Exploring Canadian Education and Labor Market Data

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1 Executive Summary

This analysis of the National Graduates Survey (NGS) 2020 transforms complex data into a clear strategic roadmap for enhancing graduate success and institutional positioning. **Our rigorous analysis of the 2020 NGS data—while mindful of its methodological constraints—**

Core Insight: A graduate's field of study is the dominant predictor of their career launch, significantly outweighing demographic factors. Our analysis reveals a clear stratification of academic programs into distinct performance tiers based on employment rates and income outcomes.

Key Findings:

- **Program Tiers are Evident:** Programs in Health, Computer Science, and Education form a top tier with employment rates exceeding 96% and strong incomes. In contrast,

programs in Arts, Humanities, and Life Sciences face more challenging market outcomes.

- **High Overall Employment:** Most graduates (93%+) find employment, demonstrating the high value of a degree.
- **Significant Income Disparity:** While the average income is $59,568, the gap between the highest and lowest-earning programs exceeds $25,000, highlighting unequal ROI across disciplines.

Strategic Imperative: This data provides a mandate for informed action. We recommend a focused strategy to promote top-tier programs, systematically enhance lower-performing ones with integrated career learning, and implement data-informed student advising to guide choices. **By leveraging these insights, with a clear understanding of the data's scope,** we can improve graduate outcomes, ensure equitable success, and strengthen our institutional value proposition in a competitive landscape.

2 Introduction

The Statistics Canada - National Graduate Survey provides a comprehensive look at the educational experiences and labour market outcomes of recent graduates in Canada. Collected in 2023, this dataset includes responses from 16,138 individuals across 114 variables, covering:

- **Demographics** (age, gender, citizenship)
- **Program details** (field of study, level of education, delivery mode)
- **Financial aid** (student loans, scholarships, funding sources)
- **Employment outcomes** (income, job relevance, satisfaction)
- **COVID-19 impacts** (program completion, career plans)

This report analyzes the NGS data to generate actionable insights for universities and policymakers, **while acknowledging the inherent data limitations and methodological considerations.** Key sections include:

1. **Data Overview**: Methodology and dataset structure.
2. **Assumptions and Limitations** : A review of data constraints and analytical parameters.
3. **Demographic Trends**: Age, gender, and citizenship distributions.
4. **Economic Outcomes**: Income disparities by field of study and region.
5. **Strategic Recommendations**: Program development, student support, and COVID-19 resilience.

Using Python (pandas, statsmodels) and interactive visualizations, this analysis highlights critical patterns to bridge the gap between education and labour market needs, **providing a transparent and robust foundation for strategic decision-making.**

3 Data Overview

3.1 National Graduates Survey- class of 2020 (Data collected in 2023)

```python
import pandas as pd
import seaborn as sns
import matplotlib as plt
from IPython.display import display, Markdown

# Read the CSV file
try:
    # Read the CSV file into a pandas DataFrame
    df = pd.read_csv('ngs2020.csv')

    # Display basic information about the dataset
    display(Markdown("<span style='color: green'>Dataset information:</span>"))
    print(f"Number of rows: {df.shape[0]}")
    print(f"Number of columns: {df.shape[1]}\n")
    df.info()
    print("\n")
    display(Markdown("<span style='color: green'>Column names:</span>"))
    print(" ".join(list(df.columns)),"\n")

    # Number of missing data
    missing_data = df.isnull().sum().sum()
    if missing_data == 0:
        print(f"\033[30;43mThere are no missing data.\033[0m")
    else:
        print(f"\033[30;43mThere are {missing_data} missing data.\033[0m")

except FileNotFoundError:
    print("Error: The file 'ngs2020.csv' was not found in the current directory.")
except pd.errors.EmptyDataError:
    print("Error: The file 'ngs2020.csv' is empty.")
except pd.errors.ParserError:
    print("Error: There was an issue parsing the CSV file. Check if it's properly formatted.
```

Dataset information:

```
Number of rows: 16138
Number of columns: 114

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16138 entries, 0 to 16137
Columns: 114 entries, PUMFID to DDIS_FL
dtypes: int64(114)
memory usage: 14.0 MB
```

Column names:

```
PUMFID CERTLEVP REG_INST REG_RESP PGMCIPAP PGM_P034 PGM_P036 PGM_P100 PGM_P111 PGM_280A PGM_
```

```
There are no missing data.
```

3.2 NGS Questions

```
import yaml
import os

# Path to the YAML file
file_path = 'ngs2020_questions.yaml'

try:
    # Open and load the YAML file
    with open(file_path, 'r') as file:
        questions = yaml.safe_load(file)

    # Print the loaded question structure

    print(f'\033[32m\nPUMFID: \033[0m Public Use Microdata File ID - {questions["PUMFID"]}\n
    print(f"Questions ({len(questions)-1}):\n")
    k = 0
    for question in questions:
      if k == 5:
        break
      else:
        if question != 'PUMFID':
            print(f'\033[32m{question}: \033[0m {questions[question]}')

except FileNotFoundError:
    print(f"Error: File '{file_path}' not found.")
except yaml.YAMLError as e:
    print(f"Error parsing YAML file: {e}")
```

```
PUMFID:  Public Use Microdata File ID - Randomly generated record identifier for the PUMF fi

Questions (113):

CERTLEVP:  2020 Program - Level of study - Grouping
REG_INST:  2020 Program - Region of postsecondary educational institution
```

REG_RESP: Time of interview 2023 - Region of primary residence

PGMCIPAP: 2020 Program - Aggregated CIP 2021

PGM_P034: 2020 Program - Full-time or part-time student

PGM_P036: 2020 Program - Reason did not take program full-time

PGM_P100: Work placement during program

PGM_P111: Work placement during prog - Description

PGM_280A: Entrepreneurial skills - Started a business

PGM_280B: Entrepreneurial skills - Completed courses

PGM_280C: Entrepreneurial skills - Business plan or pitch competition

PGM_280D: Entrepreneurial skills - Visited an entrepreneurship centre

PGM_280E: Entrepreneurial skills - Worked on an entrepreneurship project

PGM_280F: Entrepreneurial skills - None of the above

PGM_290: 2020 Program - Worked during program

PGM_350: 2020 Program - Volunteer activities during program

PGM_380: 2020 Program - Components taken outside of Canada

PGM_P401: 2020 Program - Online or distance education

PGM_410: 2020 Program - Main factor in choice of postsecondary institution

PGM_415: 2020 Program - Main factor in choice of program

PGM_430: 2020 Program - Choose the same field of study or specialization again

COV_010: COVID-19 - Completion of program delayed

COV_070: COVID-19 - Plans for further postsecondary education changed

COV_080: COVID-19 - Employment status/plans affected

EDU_010: After 2020 program - Other postsecondary programs taken

EDU_P020: After 2020 program - Number of other programs taken

HLOSINTP: Time of interview 2023 - Aggregated highest level of ed. completed

STL_010: Government-student loan program - Applied

STL_020: Government-student loan program - Applications approved

STULOANS: Government-student loan program - Received

STL_030: Government-student loan program - Main reason did not apply

OWESLGD: Government-student loan program - Debt size - Graduation 2020

OWEGVIN: Government-student loan program - Debt size - Interview 2023

STL_080: Government-student loan program - Remission/debt reduction/loan forg.

STL_100A: Received government assistance: Repayment assistance plan

STL_100B: Received government assistance: Revision of terms

STL_100C: Received government assistance: Interest only payments

STL_100D: Received government assistance: None of the above

STL_130: Government-student loan program - Total repayment term

STL_150: Government-student loan program - Repaymt of loan from financial inst.

STL_160B: Sources of funding - RESP

STL_160C: Sources of funding - Government grants or bursaries

STL_160D: Sources of funding - Non-government grants or bursaries

STL_160E: Sources of funding - Scholarships or awards

STL_160F: Sources of funding - Employment earnings or savings

STL_160G: Sources of funding - Research or teaching assistantship

STL_160H: Sources of funding - Parents, family, friends

STL_160I: Sources of funding - Bank or institution loans

STL_160J: Sources of funding - Credit cards

STL_160L: Sources of funding - Employer

STLP160N: Sources of funding - Other

SRCFUND: Sources of funding - Number of sources - All postsecondary edu

STL_170A: Main source of funding - Government student loans

STL_170B: Main source of funding - RESP

STL_170C: Main source of funding - Government grants or bursaries

STL_170D: Main source of funding - Non-government grants or bursaries

STL_170E: Main source of funding - Scholarships or awards

STL_170F: Main source of funding - Employment earnings or savings

STL_170G: Main source of funding - Research or teaching assistantship

STL_170H: Main source of funding - Parents, family, friends

STL_170I: Main source of funding - Bank or institution loans

STL_170J: Main source of funding - Credit cards

STL_170L: Main source of funding - Employer

STLP170N: Main source of funding - Other

RESPP: RESP - Total amount received for postsecondary education

STL_190: Repay loans from family or friends for education

DBTOTGRD: Loans at graduation 2020 - Debt size of non-government loans (range)

DBTALGRD: Loans at graduation 2020 - Debt size of all loans

DBTOTINT: Time of interview 2023 - Debt size of non-government loans (range)

DBTALINT: Time of interview 2023 - Debt size of all loan

SCHOLARP: Total amount received from scholarships/awards/fellowships and prizes

LMA_010: Reference week - Attended school, college, CEGEP or university

LFSTATP: Reference week - Labour force status

LMA2_07: Reference week - More than one job or business

LMA3_P01: Reference week - Employee or self-employed

LFCINDP: Reference week - Sector for job

LFCOCCP: Reference week - Broad occupational category for job

LFWFTPTP: Reference week - Full-time or part-time status of job or business

LMA6_05: Reference week - Job permanent or not permanent

LMA6_08: Reference week - Main method used to find job

JOBQLEVP: Reference week - Aggregated level of studies required to get job

JOBQLGRD: Reference week - Qualification for job compared to 2020 program

JOBQLINT: Reference week - Qualification job vs level of education

LMA6_11: Reference week - Relatedness of job or business to 2020 program

LMA6_12: Reference week - Qualification level for job

LMA6_13A: Reference week - Satisfied with overall job

LMA6_13B: Reference week - Satisfied with wage or salary of job

LMA6_13C: Reference week - Satisfied with job security

JOBINCP: Reference week - Annual wage or salary for job

LMA6_15: After program 2020 - First job

AFT_P010: After 2020 program - Number of jobs or businesses

AFT_P020: After 2020 Program - Length of time until first job or business

AFT_P040: After 2020 program - Employee or self-employed - 1st job or business

AFT_050: After 2020 program - Full-time or part-time - 1st job or business

AFT_070: After 2020 program - Permanent/not permanent - 1st job or business

AFT_080: After 2020 program - Reason job not permanent - 1st job or business

AFT_090: After 2020 program - Relatedness of 1st job/business to program

BEF_P140: Before 2020 Program - Main activity during 12 months before

BEF_160: Before 2020 program - Number of months of work experience

PREVLEVP: Before 2020 program - Aggregated highest level of studies completed

HLOSGRDP: 2020 Program - Highest level of education completed

PAR1GRD: 2020 Program - Level of education compared to that of one parent

PAR1INT: Time of interview 2023 - Level of education vs of one parent

PAR2GRD: 2020 Program - Level of education vs of the other parent

PAR2INT: Time of interview 2023 - Level of education vs that of other parent

GRADAGEP: 2020 Program - Age at time of graduation - Grouping

GENDER2: Gender after distribution of non-binary persons

MS_P01: Marital status

MS_P02: Have any dependent children

CTZSHIPP: Time of interview 2023 - Status in Canada

VISBMINP: Self-identified as a member of a visible minority group

PERSINCP: Total personal income in 2022

DDIS_FL: Disability status

3.3 Response code

```python
# Import the yaml module
from IPython.display import display, Markdown
import yaml
import os

# Check if the file exists before attempting to load it
file_path = "ngs2020_responses.yaml"

if os.path.exists(file_path):
    # Open and load the YAML file
    with open(file_path, 'r') as file:
        try:
            # Load the YAML content into a Python object (typically a dictionary)
            responses = yaml.safe_load(file)
```

```
            # Print the first few items to verify the responses loaded correctly
            display(Markdown(f"<span style='color: green'>Response code defination ({len(res
            k = 0
            for response in responses:
                if k > 3:
                    break  # print out 10 only
                print(f'\033[32m{response}:\033[0m')
                for code in responses[response]:
                    print(f'  \033[32m{code}: \033[0m{responses[response][code]}')
                k += 1

        except yaml.YAMLError as e:
            print(f"Error parsing YAML file: {e}")
else:
    print(f"File not found: {file_path}")
    print("Please make sure the file exists in the current working directory.")
    print(f"Current working directory: {os.getcwd()}")
```

Response code defination (113):

```
AFT_050:
  1: Full time
  2: Part time
  6: Valid skip
  7: Don't know
  8: Refusal
  9: Not stated
AFT_070:
  1: Permanent
  2: Not permanent
  6: Valid skip
  7: Don't know
  8: Refusal
  9: Not stated
AFT_080:
  1: Seasonal job
  2: Temporary, term or contract job
  3: Casual job
  4: Other
  6: Valid skip
  7: Don't know
  8: Refusal
  9: Not stated
AFT_090:
```

```
1: Closely related
2: Somewhat related
3: Not at all related
6: Valid skip
7: Don't know
8: Refusal
9: Not stated
```

4 Assumptions and Limitations

4.1 Assumptions

- Survey respondents accurately reported employment status, income, and educational background
- The sample (16,138 graduates) represents the broader Canadian graduate population
- Missing data codes (6, 7, 8, 9, 96-99) were appropriately handled
- Field of study (CIP codes) reliably reflects program relevance and labor market alignment

4.2 Limitations

- **Self-reported data**: Potential for recall and social desirability bias
- **Income categorization**: Midpoint approximation may not reflect exact values
- **Imbalanced classes**: Employment status skewed (93%+ employed) affecting minority class prediction
- **Limited granularity**: Program aggregation reduces detail (e.g., "Health fields" includes varied professions)
- **Regional representation**: Some subgroups may be underrepresented
- **COVID-19 impact**: Pandemic-influenced labor market may not reflect long-term trends

4.3 Methodological Constraints

- Unobserved variables (soft skills, network effects) not captured in models
- Moderate performance for minority class prediction (unemployed)
- Income prediction explains limited variance (R^2 0.295)
- Cross-sectional data limits causal inference

5 Extract All NGS Tables to Excel

```
# %run Extract_All_NGS_Tables_to_Excel.ipynb`
print("All tables saved to NGS_Tables.xlsx")
```

```
All tables saved to NGS_Tables.xlsx
```

5.1 Function for getting NGS table

```python
# Get NGS table

def get_NGS_table(table_name = 'AFT_050', excel_file="NGS_Tables.xlsx"):
    try:
        # Read the Excel sheet into a DataFrame, using first row as headers
        df = pd.read_excel(excel_file,
                           sheet_name=table_name,
                           header=0)  # header=0 is default but making it explicit
        print(f"\n'\033[32m{table_name}\033[0m': {questions[table_name]}\n")
        df
        return df
    except Exception as e:
        print(f"Error loading table {table_name}: {e}")
        return None
```

6 Dashboard

A web-based tool for exploring and visualizing data from the NGS2020 database.

6.1 Interactive Table Explorer

- Searchable list of database tables with descriptions
- Shows available tables ({ `available_count` }) and missing tables
- Table preview with sorting capabilities

6.2 Data Analysis Features

6.2.1 Statistical Summaries

- Mean, median, min, max, std dev, count

6.2.2 Automated Visualizations

- Pie/Donut charts
- Bar charts
- Box plots
- Histograms
- Weighted frequency analysis

6.3 Technical Implementation

- **Frontend**: Bootstrap 5 UI with Plotly.js visualizations
- **Backend**: Flask server with pandas/seaborn/matplotlib
- **Data Sources**:
  - `NGS_Tables_Sorted.xlsx`
  - `ngs2020_questions.yaml`

6.4 Key Functionality

- Dynamic filtering/search of tables
- Auto-generated statistics for numeric columns
- Visualizations tailored to data types
- Error handling for missing/invalid data
- Responsive design for different devices

6.5 Visual Design

- Professional blue-gradient background with animated effects
- Card-based layout with hover animations
- Data tables with striped rows and gradient headers
- Vibrant visualization color schemes

The dashboard provides researchers with an intuitive interface to explore NGS2020 survey data through both numerical summaries and visual representations, with special handling for weighted frequency distributions.

6.6 Dashboard App http://127.0.0.1:5000

7 Data Analysis & Predictive Modeling

7.1 Employment Status (Binary Classiffication)

```
import yaml
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split, cross_val_score, StratifiedKFold
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectKBest, f_classif, RFE, VarianceThreshold
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, precision_recall_curve,
from sklearn.utils.class_weight import compute_class_weight
```

```python
from imblearn.over_sampling import SMOTE
import xgboost as xgb
import warnings
import os

# Filter out the specific warnings
warnings.filterwarnings("ignore", category=UserWarning, module="sklearn.feature_selection._u
warnings.filterwarnings("ignore", category=RuntimeWarning, module="sklearn.feature_selectior

# Set professional style with a modern color palette
plt.style.use('default')
sns.set_style("whitegrid")
sns.set_palette("husl")
plt.rcParams['figure.figsize'] = (12, 8)
plt.rcParams['font.size'] = 10
plt.rcParams['axes.titlesize'] = 16
plt.rcParams['axes.titleweight'] = 'bold'
plt.rcParams['axes.labelsize'] = 12
plt.rcParams['xtick.labelsize'] = 10
plt.rcParams['ytick.labelsize'] = 10
plt.rcParams['legend.fontsize'] = 10
plt.rcParams['figure.titlesize'] = 18
plt.rcParams['figure.titleweight'] = 'bold'

# Load the YAML files with feature descriptions and response codes
def load_feature_descriptions(file_path='ngs2020_questions.yaml'):
    try:
        with open(file_path, 'r') as file:
            questions = yaml.safe_load(file)
        return questions
    except FileNotFoundError:
        print(f"Error: File '{file_path}' not found.")
        return {}
    except yaml.YAMLError as e:
        print(f"Error parsing YAML file: {e}")
        return {}

def load_response_codes(file_path='ngs2020_responses.yaml'):
    try:
        with open(file_path, 'r') as file:
            responses = yaml.safe_load(file)
        return responses
```

```
    except FileNotFoundError:
        print(f"Error: File '{file_path}' not found.")
        return {}
    except yaml.YAMLError as e:
        print(f"Error parsing YAML file: {e}")
        return {}

# Load feature descriptions and response codes
feature_descriptions = load_feature_descriptions()
response_codes = load_response_codes()

# Function to get human-readable feature names
def get_feature_name(feature_code):
    return feature_descriptions.get(feature_code, feature_code)

# Function to get human-readable response values
def get_response_value(feature_code, value):
    if feature_code in response_codes and str(value) in response_codes[feature_code]:
        return response_codes[feature_code][str(value)]
    return value

# Function to map a series to human-readable values
def map_series_to_readable(series, feature_code):
    if feature_code in response_codes:
        mapping = response_codes[feature_code]
        return series.map(lambda x: mapping.get(str(x), x))
    return series

# Function to get readable labels for plotting
def get_readable_labels(feature_code, values):
    if feature_code in response_codes:
        return [response_codes[feature_code].get(str(val), str(val)) for val in values]
    return [str(val) for val in values]

# Load the actual data
df = pd.read_csv('ngs2020.csv')

# Print available columns to help debug
print("Available columns in dataset:")
print(df.columns.tolist())

# Define missing value codes based on the data documentation
```

```python
missing_codes = [6, 7, 8, 9, 96, 97, 98, 99]

# Create a function to visualize missing data
def plot_missing_data(df):
    missing = df.isin(missing_codes).mean() * 100
    missing = missing[missing > 0]
    missing.sort_values(inplace=True)

    # Use human-readable feature names
    missing.index = [get_feature_name(col) for col in missing.index]

    # Create visualization
    fig, ax = plt.subplots(figsize=(12, 19))
    colors = plt.cm.viridis(np.linspace(0.2, 0.8, len(missing)))
    bars = ax.barh(missing.index, missing.values, color=colors, alpha=0.8, edgecolor='black'

    # Add value annotations on bars
    for bar in bars:
        width = bar.get_width()
        ax.text(width + 0.5, bar.get_y() + bar.get_height()/2,
                f'{width:.1f}%', ha='left', va='center', fontweight='bold', fontsize=10)

    # Styling
    ax.set_xlabel('Percentage (%)', fontweight='bold', fontsize=12)
    ax.set_ylabel('Column Name', fontweight='bold', fontsize=12)
    ax.set_title('Percentage of Missing/Special Values by Column',
                 fontsize=16, fontweight='bold', pad=20)

    # Add grid
    ax.grid(axis='x', alpha=0.3, linestyle='--')

    # Remove spines
    ax.spines[['top', 'right']].set_visible(False)

    # Add a subtle background
    ax.set_facecolor('#f8f9fa')

    plt.tight_layout()
    plt.show()

plot_missing_data(df)
```

```
# Data cleaning - replace missing codes with NaN
# Special handling for VISBMINP and GRADAGEP to preserve category 9 as a valid response
preserve_codes = {'VISBMINP': [9], 'GRADAGEP': [9]}  # Codes to keep as-is for specific vari

# Don't apply missing code replacement to the program column
columns_to_clean = [col for col in df.columns if col != 'PGMCIPAP']

for col in columns_to_clean:
    if df[col].dtype in ['int64', 'float64']:
        if col in preserve_codes:
            # For variables with preserved codes, only replace codes not in the preserve lis
            codes_to_replace = [c for c in missing_codes if c not in preserve_codes[col]]
            df[col] = df[col].replace(codes_to_replace, np.nan)
        else:
            # For all other variables, replace all missing codes
            df[col] = df[col].replace(missing_codes, np.nan)

# For the program column, only replace the actual missing codes (96, 97, 98, 99)
if 'PGMCIPAP' in df.columns:
    df['PGMCIPAP'] = df['PGMCIPAP'].replace([96, 97, 98, 99], np.nan)

# Employment Status Analysis
def employment_analysis(df):
    print("\n=== Employment Status Analysis ===\n")

    if 'LFSTATP' not in df.columns:
        print("Employment status data not available.")
        return

    # Create a figure for employment status plots
    fig, axes = plt.subplots(1, 2, figsize=(16, 6))

    # Color palette
    colors = sns.color_palette("husl", 8)

    # Employment status distribution
    # Ensure we include all expected categories
    employment_counts = df['LFSTATP'].value_counts(dropna=False)
    employment_labels = get_readable_labels('LFSTATP', employment_counts.index)

    print(f"{get_feature_name('LFSTATP')} Distribution:")
    for label, count in zip(employment_labels, employment_counts):
```

```
    print(f"{label}: {count}")

# Create pie chart for employment status
explode = [0.05] * len(employment_counts)  # explode slices for emphasis
wedges, texts, autotexts = axes[0].pie(employment_counts, labels=employment_labels, autc
                                       colors=colors[:len(employment_counts)], startangle
                                       shadow=True, textprops={'fontsize': 10})

# Style the pie chart
for autotext in autotexts:
    autotext.set_color('white')
    autotext.set_fontweight('bold')
    autotext.set_fontsize(10)

axes[0].set_title(f'{get_feature_name("LFSTATP")} Distribution', fontweight='bold', font
axes[0].axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle

# Employment status by education level
if 'CERTLEVP' in df.columns:
    # Create cross-tabulation
    emp_by_edu = pd.crosstab(df['CERTLEVP'], df['LFSTATP'])

    # Convert to percentages
    emp_by_edu_pct = emp_by_edu.div(emp_by_edu.sum(axis=1), axis=0) * 100

    # Get readable labels
    edu_labels = get_readable_labels('CERTLEVP', emp_by_edu_pct.index)
    emp_labels = get_readable_labels('LFSTATP', emp_by_edu_pct.columns)

    # Create stacked bar chart
    bottom = np.zeros(len(edu_labels))
    for i, emp_status in enumerate(emp_by_edu_pct.columns):
        axes[1].bar(edu_labels, emp_by_edu_pct[emp_status], bottom=bottom,
                   label=emp_labels[i], color=colors[i], alpha=0.8, edgecolor='black', l
        bottom += emp_by_edu_pct[emp_status]

    axes[1].set_title('Employment Status by Education Level', fontweight='bold', fontsiz
    axes[1].set_ylabel('Percentage (%)', fontweight='bold', fontsize=12)
    axes[1].tick_params(axis='x', rotation=45)
    axes[1].legend(bbox_to_anchor=(1.05, 1), loc='upper left')

    # Add grid
```

```
        axes[1].grid(axis='y', alpha=0.3, linestyle='--')

        # Remove spines
        axes[1].spines[['top', 'right']].set_visible(False)
    else:
        axes[1].set_visible(False)
        print("Education level data (CERTLEVP) not available for employment analysis.")

    # Add a background color to the figure
    fig.patch.set_facecolor('#f8f9fa')

    plt.tight_layout()
    plt.show()

employment_analysis(df)

# Correlation Analysis with Employment Focus
def correlation_analysis(df):
    print("\n=== Correlation Analysis ===\n")

    # Select columns that might have meaningful correlations with employment
    corr_cols = [
        'GRADAGEP',
        'PERSINCP',
        'JOBINCP',
        'STULOANS',
        'LFSTATP',
        'CERTLEVP',
    ]

    # Add additional columns if they exist
    optional_cols = ['LFCINDP', 'LFCOCCP', 'COV_010']
    for col in optional_cols:
        if col in df.columns:
            corr_cols.append(col)

    # Filter to only include columns that exist in the dataset
    corr_cols = [col for col in corr_cols if col in df.columns]

    if len(corr_cols) < 2:
        print("Not enough columns for correlation analysis.")
        return
```

```
corr_df = df[corr_cols].copy()

# Filter out missing codes
for col in corr_cols:
    corr_df = corr_df[~corr_df[col].isin(missing_codes)]

# Compute correlation matrix
corr_matrix = corr_df.corr()

# Get human-readable labels
human_labels = [get_feature_name(col) for col in corr_cols]

# Plot heatmap
plt.figure(figsize=(12, 10))

# Create a mask for the upper triangle
mask = np.triu(np.ones_like(corr_matrix, dtype=bool))

# Create heatmap with mask
heatmap = sns.heatmap(
    corr_matrix,
    annot=True,
    cmap='RdBu_r',
    center=0,
    fmt=".2f",
    square=True,
    mask=mask,
    cbar_kws={"shrink": 0.8},
    annot_kws={"size": 11, "weight": "bold"},
    linewidths=0.5,
    linecolor='white'
)

# Set title
plt.title('Correlation Matrix of Key Variables (Employment Focus)', fontsize=16, fontwei

# Set x-axis labels with rotation
heatmap.set_xticklabels(human_labels, rotation=30, ha='right', fontsize=18)

# Set y-axis labels with proper rotation and alignment
heatmap.set_yticklabels(human_labels, rotation=0, va='center', fontsize=18)
```

```
    # Add a background
    plt.gca().set_facecolor('#f8f9fa')

    plt.tight_layout()
    plt.show()

correlation_analysis(df)

# Define potential features for employment prediction modeling
potential_features = [
    'GENDER2', 'CERTLEVP', 'PERSINCP', 'GRADAGEP',
    'VISBMINP', 'CTZSHIPP', 'MS_P01', 'REG_INST', 'EDU_010',
    'PGMCIPAP', 'STULOANS', 'JOBINCP'
]

# Add optional features if they exist in the dataset
optional_features = ['LFCINDP', 'LFCOCCP', 'LMA6_11', 'COV_010', 'LMA_010', 'LMA_020', 'LMA_
for feature in optional_features:
    if feature in df.columns:
        potential_features.append(feature)

# Filter to only include columns that exist in the dataset
potential_features = [col for col in potential_features if col in df.columns]

print(f"Using the following features for modeling: {potential_features}")

# Predictive Modeling with Feature Selection for Employment
def predict_employment(df, features):
    print("\n=== Predictive Modeling: Employment Status Prediction ===\n")

    if 'LFSTATP' not in df.columns:
        print("Employment status (LFSTATP) not available for modeling.")
        return

    # Remove job-related features that are 100% missing for unemployed individuals
    job_features_to_remove = ['JOBINCP', 'LFCINDP', 'LFCOCCP', 'LMA6_11']
    features = [f for f in features if f not in job_features_to_remove]
    print(f"Removed job-related features: {job_features_to_remove}")
    print(f"Using features: {[get_feature_name(f) for f in features]}")

    # Prepare data with potential features
    model_df = df[features + ['LFSTATP']].copy()
```

```
# Replace missing codes with NaN
for col in model_df.columns:
    if model_df[col].dtype in ['int64', 'float64']:
        if col in preserve_codes:
            codes_to_replace = [c for c in missing_codes if c not in preserve_codes[col]
            model_df[col] = model_df[col].replace(codes_to_replace, np.nan)
        else:
            model_df[col] = model_df[col].replace(missing_codes, np.nan)

# Filter for employed and unemployed only
model_df = model_df[model_df['LFSTATP'].isin([1, 2])]

# Drop rows with missing values
model_df = model_df.dropna()

# Check class distribution
class_counts = model_df['LFSTATP'].value_counts()
print(f"Class distribution after processing: {dict(class_counts)}")

if len(class_counts) < 2:
    print("Warning: Still only one class after removing job-related features.")
    print("This suggests other features are still causing issues.")
    return

if len(model_df) < 100:
    print(f"Not enough data for modeling. Only {len(model_df)} samples available.")
    return

# Convert categorical variables to numerical
le = LabelEncoder()
for col in features:
    if model_df[col].dtype == 'object':
        model_df[col] = le.fit_transform(model_df[col])

# Split data with stratification
X = model_df.drop('LFSTATP', axis=1)
y = model_df['LFSTATP']
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y
)

# Remove constant features
```

```
    selector = VarianceThreshold()
    X_train_clean = selector.fit_transform(X_train)
    X_test_clean = selector.transform(X_test)

    # Get the feature names after removing constant features
    selected_features = X.columns[selector.get_support()]
    X_train = pd.DataFrame(X_train_clean, columns=selected_features)
    X_test = pd.DataFrame(X_test_clean, columns=selected_features)

    if len(selected_features) == 0:
        print("No features remaining after variance threshold. Cannot proceed with modeling.
        return

    # Calculate class weights for imbalanced data
    classes = np.unique(y_train)
    class_weights = compute_class_weight('balanced', classes=classes, y=y_train)
    class_weight_dict = dict(zip(classes, class_weights))
    print(f"Class weights: {class_weight_dict}")

    # Apply SMOTE to balance the training data
    smote = SMOTE(random_state=42)
    X_train_res, y_train_res = smote.fit_resample(X_train, y_train)
    print(f"After SMOTE - Class distribution: {np.bincount(y_train_res)}")

    # Feature Selection Methods (using resampled data)
    # Method 1: SelectKBest with ANOVA F-value
    print("1. SelectKBest Feature Selection:")
    k = min(5, len(selected_features))
    selector_kbest = SelectKBest(score_func=f_classif, k=k)
    X_kbest = selector_kbest.fit_transform(X_train_res, y_train_res)
    selected_features_kbest = selected_features[selector_kbest.get_support()]
    selected_features_kbest_desc = [get_feature_name(feat) for feat in selected_features_kbe
    print(f"Selected features: {selected_features_kbest_desc}")

    # Method 2: Recursive Feature Elimination (RFE)
    print("\n2. Recursive Feature Elimination (RFE):")
    estimator = LogisticRegression(random_state=42, max_iter=1000, class_weight='balanced')
    n_features = min(5, len(selected_features))
    selector_rfe = RFE(estimator, n_features_to_select=n_features, step=1)
    X_rfe = selector_rfe.fit_transform(X_train_res, y_train_res)
    selected_features_rfe = selected_features[selector_rfe.get_support()]
    selected_features_rfe_desc = [get_feature_name(feat) for feat in selected_features_rfe]
```

```
print(f"Selected features: {selected_features_rfe_desc}")

# Method 3: Feature Importance from Random Forest
print("\n3. Random Forest Feature Importance:")
rf = RandomForestClassifier(random_state=42, class_weight='balanced')
rf.fit(X_train_res, y_train_res)

# Plot feature importance
importance = pd.Series(rf.feature_importances_, index=selected_features)
importance.index = [get_feature_name(feat) for feat in importance.index]
importance = importance.sort_values(ascending=True)

# Create a horizontal bar chart for feature importance
plt.figure(figsize=(12, 10))
colors = plt.cm.viridis(np.linspace(0.2, 0.8, len(importance)))
bars = plt.barh(importance.index, importance.values, color=colors, alpha=0.8, edgecolor=

# Add value annotations on bars
for bar in bars:
    width = bar.get_width()
    plt.text(width + 0.001, bar.get_y() + bar.get_height()/2,
            f'{width:.3f}', ha='left', va='center', fontweight='bold', fontsize=10)

# Styling
plt.xlabel('Importance Score', fontweight='bold', fontsize=12)
plt.ylabel('Features', fontweight='bold', fontsize=12)
plt.title('Feature Importance for Employment Status Prediction', fontsize=16, fontweight

# Add grid
plt.grid(axis='x', alpha=0.3, linestyle='--')

# Remove spines
plt.gca().spines[['top', 'right']].set_visible(False)

# Add a background
plt.gca().set_facecolor('#f8f9fa')

plt.tight_layout()
plt.show()

# Select top 5 features based on importance
top_features = importance.nlargest(min(5, len(importance))).index.tolist()
```

```
print(f"Top 5 features: {top_features}")

# Compare performance with and without feature selection
print("\n4. Model Performance Comparison:")

# Baseline model (all features)
model_all = RandomForestClassifier(random_state=42, class_weight='balanced')
model_all.fit(X_train_res, y_train_res)
y_pred_all = model_all.predict(X_test)
accuracy_all = model_all.score(X_test, y_test)
print("All features accuracy:", accuracy_all)

# Model with top 5 features from RF importance
top_feature_codes = [feat for feat in selected_features if get_feature_name(feat) in top
X_train_top = X_train_res[top_feature_codes]
X_test_top = X_test[top_feature_codes]

model_top = RandomForestClassifier(random_state=42, class_weight='balanced')
model_top.fit(X_train_top, y_train_res)
y_pred_top = model_top.predict(X_test_top)
accuracy_top = model_top.score(X_test_top, y_test)
print("Top 5 features accuracy:", accuracy_top)

# Model with SelectKBest features
X_train_kbest = X_train_res[selected_features_kbest]
X_test_kbest = X_test[selected_features_kbest]

model_kbest = RandomForestClassifier(random_state=42, class_weight='balanced')
model_kbest.fit(X_train_kbest, y_train_res)
y_pred_kbest = model_kbest.predict(X_test_kbest)
accuracy_kbest = model_kbest.score(X_test_kbest, y_test)
print("SelectKBest features accuracy:", accuracy_kbest)

# Model with RFE features
X_train_rfe = X_train_res[selected_features_rfe]
X_test_rfe = X_test[selected_features_rfe]

model_rfe = RandomForestClassifier(random_state=42, class_weight='balanced')
model_rfe.fit(X_train_rfe, y_train_res)
y_pred_rfe = model_rfe.predict(X_test_rfe)
accuracy_rfe = model_rfe.score(X_test_rfe, y_test)
print("RFE features accuracy:", accuracy_rfe)
```

```
# Create a comparison chart
methods = ['All Features', 'Top 5 Features', 'SelectKBest', 'RFE']
accuracies = [accuracy_all, accuracy_top, accuracy_kbest, accuracy_rfe]

# Create a comparison bar chart
plt.figure(figsize=(5, 2))
colors = ['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728']
bars = plt.bar(methods, accuracies, color=colors, alpha=0.8, edgecolor='black', linewidt

# Add value labels on top of bars
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2., height + 0.01,
            f'{height:.3f}', ha='center', va='bottom', fontweight='bold', fontsize=11)

# Styling
plt.ylabel('Accuracy', fontweight='bold', fontsize=12)
plt.title('Model Accuracy', fontsize=12, fontweight='bold', pad=20)
plt.ylim(0, 1)

# Add grid
plt.grid(axis='y', alpha=0.3, linestyle='--')

# Remove spines
plt.gca().spines[['top', 'right']].set_visible(False)

# Add a background
plt.gca().set_facecolor('#f8f9fa')

plt.tight_layout()
plt.show()

# Compare classification reports
print("\nClassification Report - All Features:")
print(classification_report(y_test, y_pred_all))

print("Classification Report - Top 5 Features:")
print(classification_report(y_test, y_pred_top))

# Create confusion matrix for the best model
best_model = model_top  # Using top features model
y_pred_best = best_model.predict(X_test_top)
```

```
cm = confusion_matrix(y_test, y_pred_best)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Employed', 'Unemployed'],
            yticklabels=['Employed', 'Unemployed'])
plt.title('Confusion Matrix - Employment Prediction', fontsize=16, fontweight='bold', pa
plt.ylabel('Actual', fontweight='bold')
plt.xlabel('Predicted', fontweight='bold')
plt.tight_layout()
plt.show()

# Plot Precision-Recall curve for the minority class
y_prob = best_model.predict_proba(X_test_top)[:, 1]  # Probability for class 2 (unemploy
precision, recall, thresholds = precision_recall_curve(y_test-1, y_prob)  # Convert to (

plt.figure(figsize=(10, 8))
plt.plot(recall, precision, marker='.', label='Random Forest')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve for Minority Class (Unemployed)', fontsize=16, fontwei
plt.legend()

# Calculate AUC
pr_auc = auc(recall, precision)
print(f"Precision-Recall AUC: {pr_auc:.3f}")

# Find optimal threshold (maximizing F1-score)
f1_scores = 2 * (precision * recall) / (precision + recall + 1e-10)
optimal_idx = np.argmax(f1_scores)
optimal_threshold = thresholds[optimal_idx]
optimal_precision = precision[optimal_idx]
optimal_recall = recall[optimal_idx]

plt.plot(optimal_recall, optimal_precision, 'ro', markersize=10,
         label=f'Optimal Threshold ({optimal_threshold:.2f})')
plt.legend()
plt.grid(True)
plt.show()

print(f"Optimal Threshold: {optimal_threshold:.3f}")
print(f"Optimal Precision: {optimal_precision:.3f}")
print(f"Optimal Recall: {optimal_recall:.3f}")
```

```
# Apply optimal threshold
y_pred_optimal = (y_prob >= optimal_threshold).astype(int) + 1  # Convert back to 1/2

print("\nClassification Report with Optimal Threshold:")
print(classification_report(y_test, y_pred_optimal))

# Add XGBoost model after the Random Forest models
print("\n6. XGBoost Model with Class Weighting:")

# Convert labels from [1, 2] to [0, 1] for XGBoost
y_train_xgb = y_train_res - 1
y_test_xgb = y_test - 1

# Calculate the ratio for scale_pos_weight
count_majority = (y_train == 1).sum()
count_minority = (y_train == 2).sum()
ratio = count_majority / count_minority
print(f"Class ratio (majority:minority): {ratio:.2f}:1")

# XGBoost model
xgb_model = xgb.XGBClassifier(
    random_state=42,
    scale_pos_weight=ratio,
    eval_metric='logloss'
)
xgb_model.fit(X_train_res[top_feature_codes], y_train_xgb)
y_pred_xgb = xgb_model.predict(X_test_top)

# Convert predictions back to original labels [1, 2]
y_pred_xgb_original = y_pred_xgb + 1

print("XGBoost Classification Report:")
print(classification_report(y_test, y_pred_xgb_original))

# Plot XGBoost feature importance
plt.figure(figsize=(12, 10))
xgb_importance = pd.Series(xgb_model.feature_importances_, index=top_feature_codes)
xgb_importance.index = [get_feature_name(feat) for feat in xgb_importance.index]
xgb_importance = xgb_importance.sort_values(ascending=True)

colors = plt.cm.viridis(np.linspace(0.2, 0.8, len(xgb_importance)))
bars = plt.barh(xgb_importance.index, xgb_importance.values, color=colors, alpha=0.8, ed
```

```
    # Add value annotations on bars
    for bar in bars:
        width = bar.get_width()
        plt.text(width + 0.001, bar.get_y() + bar.get_height()/2,
                f'{width:.3f}', ha='left', va='center', fontweight='bold', fontsize=10)

    plt.xlabel('Importance Score', fontweight='bold', fontsize=12)
    plt.ylabel('Features', fontweight='bold', fontsize=12)
    plt.title('XGBoost Feature Importance', fontsize=16, fontweight='bold', pad=20)
    plt.grid(axis='x', alpha=0.3, linestyle='--')
    plt.gca().spines[['top', 'right']].set_visible(False)
    plt.gca().set_facecolor('#f8f9fa')
    plt.tight_layout()
    plt.show()

    # Cross-validation to validate results
    print("\n7. Cross-Validation Results:")
    cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
    cv_scores = cross_val_score(model_top, X_train_res[top_feature_codes], y_train_res,
                               cv=cv, scoring='f1_weighted')
    print(f"Cross-Validation F1 Scores: {cv_scores}")
    print(f"Mean CV F1 Score: {cv_scores.mean():.3f} (+/- {cv_scores.std() * 2:.3f})")

# Run predictive modeling with the fixed function
predict_employment(df, potential_features)

# Additional analysis: Employment outcomes by program
def employment_by_program(df):
    print("\n=== Employment Outcomes by Program ===\n")

    if 'PGMCIPAP' not in df.columns or 'LFSTATP' not in df.columns:
        print("Program or employment data not available.")
        return

    # Create cross-tabulation of program vs employment status
    program_emp = pd.crosstab(df['PGMCIPAP'], df['LFSTATP'])

    # Filter for programs with sufficient data
    program_emp = program_emp[program_emp.sum(axis=1) > 50]

    if len(program_emp) == 0:
        print("Insufficient data for program employment analysis.")
```

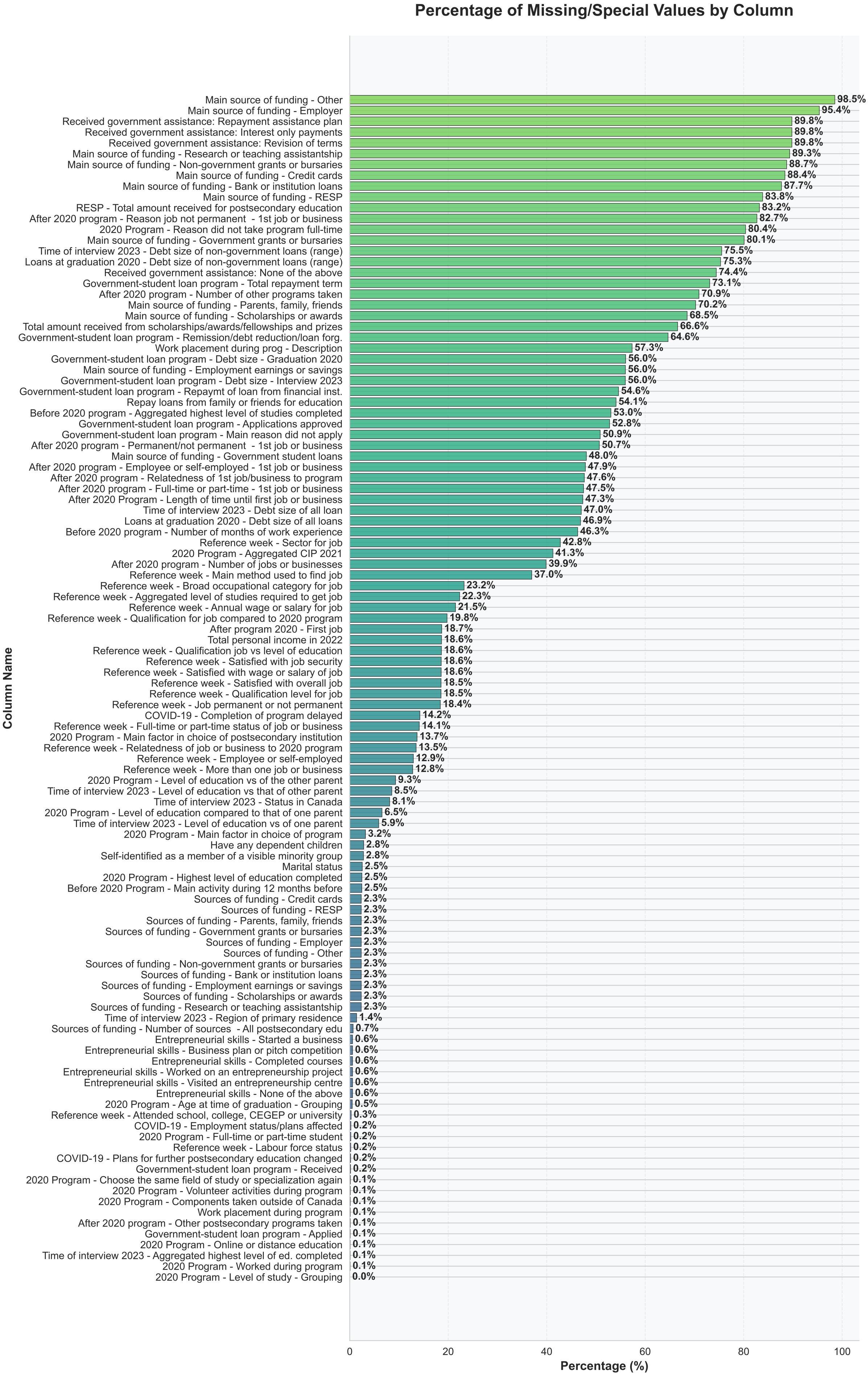
```
    return

# Calculate employment rate (employed / (employed + unemployed))
program_emp['Employment_Rate'] = program_emp[1] / (program_emp[1] + program_emp[2]) * 10

# Sort by employment rate
program_emp = program_emp.sort_values('Employment_Rate', ascending=False)

# Get all programs (not just top/bottom 10 since we have only 5)
all_programs = program_emp.copy()

# Create visualization
fig, ax = plt.subplots(figsize=(14, 8))

# Get program names - convert program codes to strings for lookup
program_labels = []
for pid in all_programs.index:
    # Convert program code to string for lookup
    program_code_str = str(int(pid)) if pid.is_integer() else str(pid)
    program_name = get_response_value('PGMCIPAP', program_code_str)
    if program_name == program_code_str:  # If no description found, use generic name
        program_name = f"Program {pid}"
    program_labels.append(program_name)

# Create bar chart
colors = plt.cm.viridis(np.linspace(0.2, 0.8, len(all_programs)))
bars = ax.barh(range(len(all_programs)), all_programs['Employment_Rate'],
               color=colors, alpha=0.8, edgecolor='black', linewidth=0.5)

ax.set_yticks(range(len(all_programs)))
ax.set_yticklabels(program_labels, fontsize=18)
ax.set_xlabel('Employment Rate (%)', fontweight='bold')
ax.set_title('Employment Rate by Program', fontsize=16, fontweight='bold', pad=20)
ax.invert_yaxis()  # Highest employment at the top

# Add value labels
for i, bar in enumerate(bars):
    width = bar.get_width()
    ax.text(width + 0.5, bar.get_y() + bar.get_height()/2,
            f'{width:.1f}%', ha='left', va='center', fontweight='bold')

# Add grid
ax.grid(axis='x', alpha=0.3, linestyle='--')
```

```
    # Remove spines
    ax.spines[['top', 'right']].set_visible(False)

    plt.tight_layout()
    plt.show()

    # Print the results with more information
    print("Programs by Employment Rate (with sufficient data):")
    for pid, row in all_programs.iterrows():
        # Convert program code to string for lookup
        program_code_str = str(int(pid)) if pid.is_integer() else str(pid)
        program_name = get_response_value('PGMCIPAP', program_code_str)
        if program_name == program_code_str:  # If no description found, use generic name
            program_name = f"Program {pid}"

        # Use .iloc to avoid the warning about position-based indexing
        employed = row.iloc[0]  # First column (employed)
        unemployed = row.iloc[1]  # Second column (unemployed)
        total = employed + unemployed
        rate = row['Employment_Rate']

        print(f"{program_name}: {rate:.1f}% ({employed}/{total} employed)")

    # Provide additional context
    print(f"\nNote: Only {len(all_programs)} programs had sufficient data (>50 respondents)'

# Run the program analysis
employment_by_program(df)

# Employment Income Heatmap by Region and Program with Mapped Labels
def employment_income_heatmap(df):
    print("\n=== Employment Income Heatmap (JOBINCP) ===\n")

    # Check necessary columns
    if 'JOBINCP' not in df.columns or 'REG_RESP' not in df.columns or 'PGMCIPAP' not in df.c
        print("Required columns for income heatmap not available.")
        return

    # Filter for employed individuals only
    employed_df = df[df['LFSTATP'] == 1].copy()

    # Map JOBINCP codes to midpoint values
```

```
income_mapping = {
    1: 15000,    # Under $30000 (midpoint)
    2: 40000,    # $30000-$49999
    3: 60000,    # $50000-$69999
    4: 80000,    # $70000-$89999
    5: 95000     # $90000+ (approximate midpoint)
}

# Map region codes to region names
region_mapping = {
    1: "Atlantic provinces",
    2: "Quebec",
    3: "Ontario",
    4: "Western provinces territories"
}

# Map program codes to program names
program_mapping = {
    1: "Education",
    4: "Social/behavioral sciences/law",
    5: "Business/management/public admin",
    6: "Physical/life sciences/technologies",
    7: "Math/computer/info sciences",
    8: "Architecture/engineering/trades",
    9: "Health fields",
    10: "Other"
}

employed_df['INCOME_MIDPOINT'] = employed_df['JOBINCP'].map(income_mapping)
employed_df['REGION_NAME'] = employed_df['REG_RESP'].map(region_mapping)
employed_df['PROGRAM_NAME'] = employed_df['PGMCIPAP'].map(program_mapping)

# Remove rows with missing income, region, or program data
employed_df = employed_df.dropna(subset=['INCOME_MIDPOINT', 'REGION_NAME', 'PROGRAM_NAME

# Group by region and program, calculate mean income
income_by_region_program = employed_df.groupby(['REGION_NAME', 'PROGRAM_NAME'])['INCOME_

# Create heatmap
plt.figure(figsize=(16, 12))
ax = sns.heatmap(
    income_by_region_program,
```

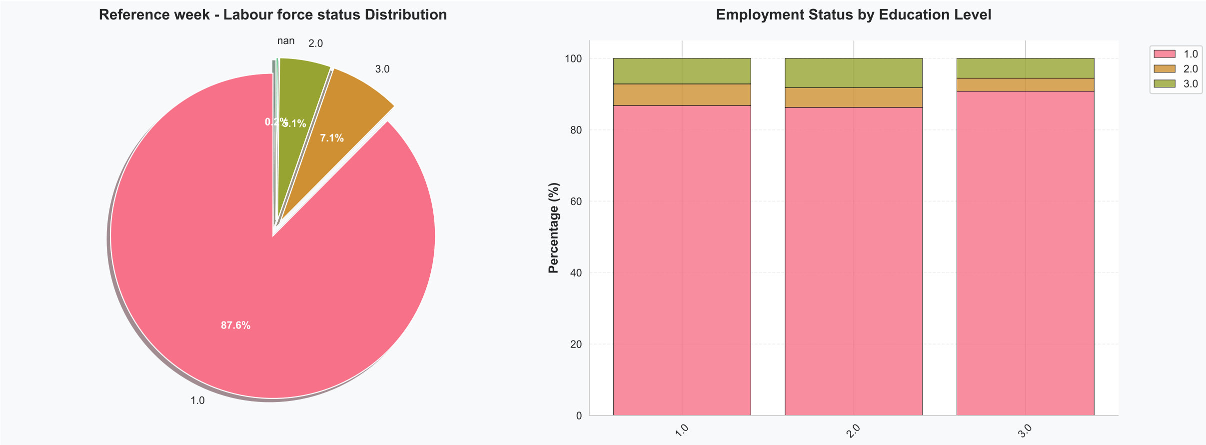
```
        annot=True,
        fmt=".0f",
        cmap="YlGnBu",
        cbar_kws={'label': 'Average Income ($)'},
        linewidths=0.5,
        linecolor='grey'
    )

    # Set colorbar label size
    cbar = ax.collections[0].colorbar
    cbar.ax.set_ylabel('Average Income ($)', fontsize=20)
    cbar.ax.tick_params(labelsize=20)

    plt.title('Average Employment Income by Region and Program\n(JOBINCP Midpoint Values)',
              fontsize=24, fontweight='bold', pad=20)
    plt.xlabel('Program', fontweight='bold', fontsize=20)
    plt.ylabel('Region', fontweight='bold', fontsize=20)

    # Set tick label size to 20
    ax.set_xticklabels(ax.get_xticklabels(), fontsize=20)
    ax.set_yticklabels(ax.get_yticklabels(), fontsize=20)

    # Rotate x-axis labels for better readability
    plt.xticks(rotation=45, ha='right')
    plt.yticks(rotation=45, ha='right')
    # Adjust layout
    plt.tight_layout()
    plt.show()

    # Print some summary statistics
    print("Summary Statistics:")
    print(f"Total employed individuals in analysis: {len(employed_df)}")
    print(f"Average income across all employed: ${employed_df['INCOME_MIDPOINT'].mean():.0f}
    print(f"Highest paying region-program combination: ${income_by_region_program.max().max(
    print(f"Lowest paying region-program combination: ${income_by_region_program.min().min()

# Call the function
employment_income_heatmap(df)
```

```
Available columns in dataset:
['PUMFID', 'CERTLEVP', 'REG_INST', 'REG_RESP', 'PGMCIPAP', 'PGM_P034', 'PGM_P036', 'PGM_P10C
```

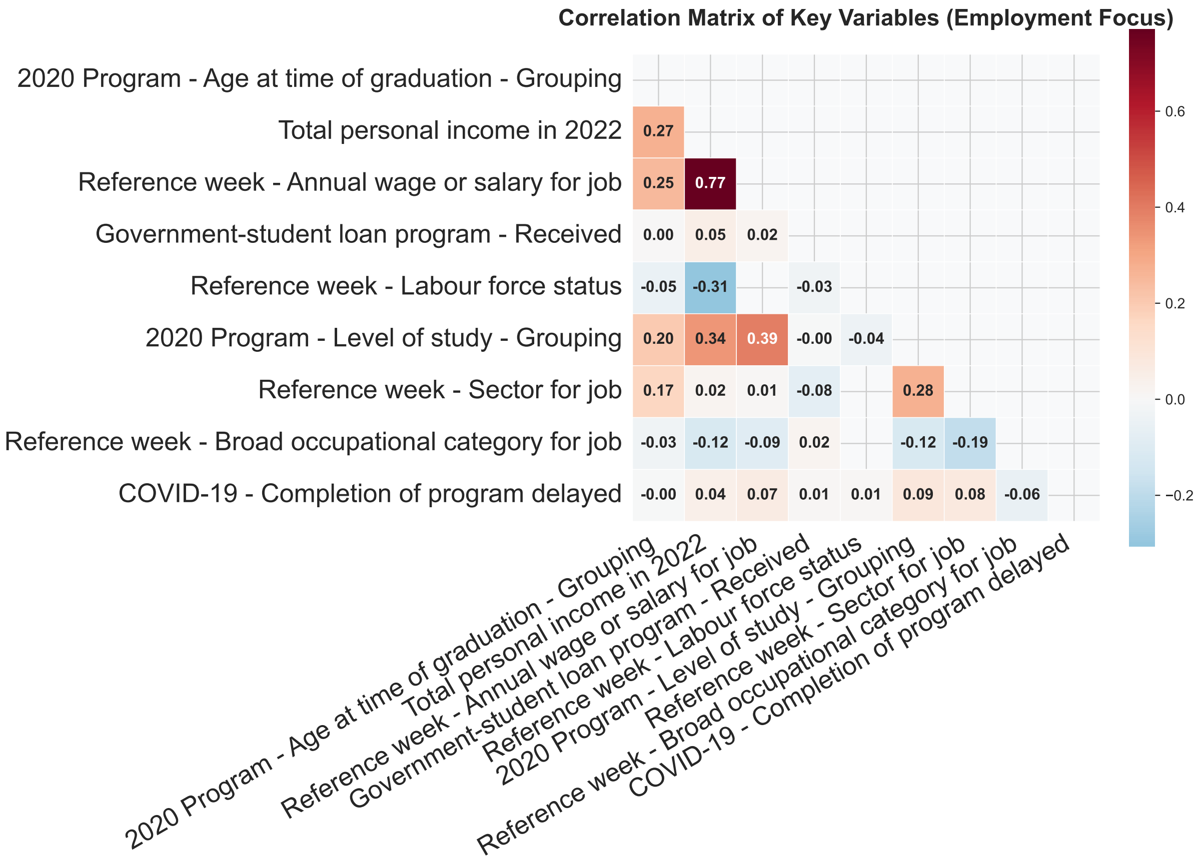


Percentage of Missing/Special Values by Column
Column Name
Percentage (%)
0
20
40
60
80
100
Main source of funding - Other 98.5%
Main source of funding - Employer 95.4%
Received government assistance: Repayment assistance plan 89.8%
Received government assistance: Interest only payments 89.8%
Received government assistance: Revision of terms 89.8%
Main source of funding - Research or teaching assistantship 89.3%
Main source of funding - Non-government grants or bursaries 88.7%
Main source of funding - Credit cards 88.4%
Main source of funding - Bank or institution loans 87.7%
Main source of funding - RESP 83.8%
RESP - Total amount received for postsecondary education 83.2%
After 2020 program - Reason job not permanent - 1st job or business 82.7%
2020 Program - Reason did not take program full-time 80.4%
Main source of funding - Government grants or bursaries 80.1%
Time of interview 2023 - Debt size of non-government loans (range) 75.5%
Loans at graduation 2020 - Debt size of non-government loans (range) 75.3%
Received government assistance: None of the above 74.4%
Government-student loan program - Total repayment term 73.1%
After 2020 program - Number of other programs taken 70.9%
Main source of funding - Parents, family, friends 70.2%
Main source of funding - Scholarships or awards 68.5%
Total amount received from scholarships/awards/fellowships and prizes 66.6%
Government-student loan program - Remission/debt reduction/loan forg. 64.6%
Work placement during prog - Description 57.3%
Government-student loan program - Debt size - Graduation 2020 56.0%
Main source of funding - Employment earnings or savings 56.0%
Government-student loan program - Debt size - Interview 2023 56.0%
Government-student loan program - Repaymt of loan from financial inst. 54.6%
Repay loans from family or friends for education 54.1%
Before 2020 program - Aggregated highest level of studies completed 53.0%
Government-student loan program - Applications approved 52.8%
Government-student loan program - Main reason did not apply 50.9%
After 2020 program - Permanent/not permanent - 1st job or business 50.7%
Main source of funding - Government student loans 48.0%
After 2020 program - Employee or self-employed - 1st job or business 47.9%
After 2020 program - Relatedness of 1st job/business to program 47.6%
After 2020 program - Full-time or part-time - 1st job or business 47.5%
After 2020 Program - Length of time until first job or business 47.3%
Time of interview 2023 - Debt size of all loan 47.0%
Loans at graduation 2020 - Debt size of all loans 46.9%
Before 2020 program - Number of months of work experience 46.3%
Reference week - Sector for job 42.8%
2020 Program - Aggregated CIP 2021 41.3%
After 2020 program - Number of jobs or businesses 39.9%
Reference week - Main method used to find job 37.0%
Reference week - Broad occupational category for job 23.2%
Reference week - Aggregated level of studies required to get job 22.3%
Reference week - Annual wage or salary for job 21.5%
Reference week - Qualification for job compared to 2020 program 19.8%
After program 2020 - First job 18.7%
Total personal income in 2022 18.6%
Reference week - Qualification job vs level of education 18.6%
Reference week - Satisfied with job security 18.6%
Reference week - Satisfied with wage or salary of job 18.6%
Reference week - Satisfied with overall job 18.5%
Reference week - Qualification level for job 18.5%
Reference week - Job permanent or not permanent 18.4%
COVID-19 - Completion of program delayed 14.2%
Reference week - Full-time or part-time status of job or business 14.1%
2020 Program - Main factor in choice of postsecondary institution 13.7%
Reference week - Relatedness of job or business to 2020 program 13.5%
Reference week - Employee or self-employed 12.9%
Reference week - More than one job or business 12.8%
2020 Program - Level of education vs of the other parent 9.3%
Time of interview 2023 - Level of education vs that of other parent 8.5%
Time of interview 2023 - Status in Canada 8.1%
2020 Program - Level of education compared to that of one parent 6.5%
Time of interview 2023 - Level of education vs of one parent 5.9%
2020 Program - Main factor in choice of program 3.2%
Have any dependent children 2.8%
Self-identified as a member of a visible minority group 2.8%
Marital status 2.5%
2020 Program - Highest level of education completed 2.5%
Before 2020 Program - Main activity during 12 months before 2.5%
Sources of funding - Credit cards 2.3%
Sources of funding - RESP 2.3%
Sources of funding - Parents, family, friends 2.3%
Sources of funding - Government grants or bursaries 2.3%
Sources of funding - Employer 2.3%
Sources of funding - Other 2.3%
Sources of funding - Non-government grants or bursaries 2.3%
Sources of funding - Bank or institution loans 2.3%
Sources of funding - Employment earnings or savings 2.3%
Sources of funding - Scholarships or awards 2.3%
Sources of funding - Research or teaching assistantship 2.3%
Time of interview 2023 - Region of primary residence 1.4%
Sources of funding - Number of sources - All postsecondary edu 0.7%
Entrepreneurial skills - Started a business 0.6%
Entrepreneurial skills - Business plan or pitch competition 0.6%
Entrepreneurial skills - Completed courses 0.6%
Entrepreneurial skills - Worked on an entrepreneurship project 0.6%
Entrepreneurial skills - Visited an entrepreneurship centre 0.6%
Entrepreneurial skills - None of the above 0.6%
2020 Program - Age at time of graduation - Grouping 0.5%
Reference week - Attended school, college, CEGEP or university 0.3%
COVID-19 - Employment status/plans affected 0.2%
2020 Program - Full-time or part-time student 0.2%
Reference week - Labour force status 0.2%
COVID-19 - Plans for further postsecondary education changed 0.2%
Government-student loan program - Received 0.2%
2020 Program - Choose the same field of study or specialization again 0.1%
2020 Program - Volunteer activities during program 0.1%
2020 Program - Components taken outside of Canada 0.1%
Work placement during program 0.1%
After 2020 program - Other postsecondary programs taken 0.1%
Government-student loan program - Applied 0.1%
2020 Program - Online or distance education 0.1%
Time of interview 2023 - Aggregated highest level of ed. completed 0.1%
2020 Program - Worked during program 0.1%
2020 Program - Level of study - Grouping 0.0%

```
=== Employment Status Analysis ===

Reference week - Labour force status Distribution:
1.0: 14129
3.0: 1147
2.0: 829
nan: 33
```

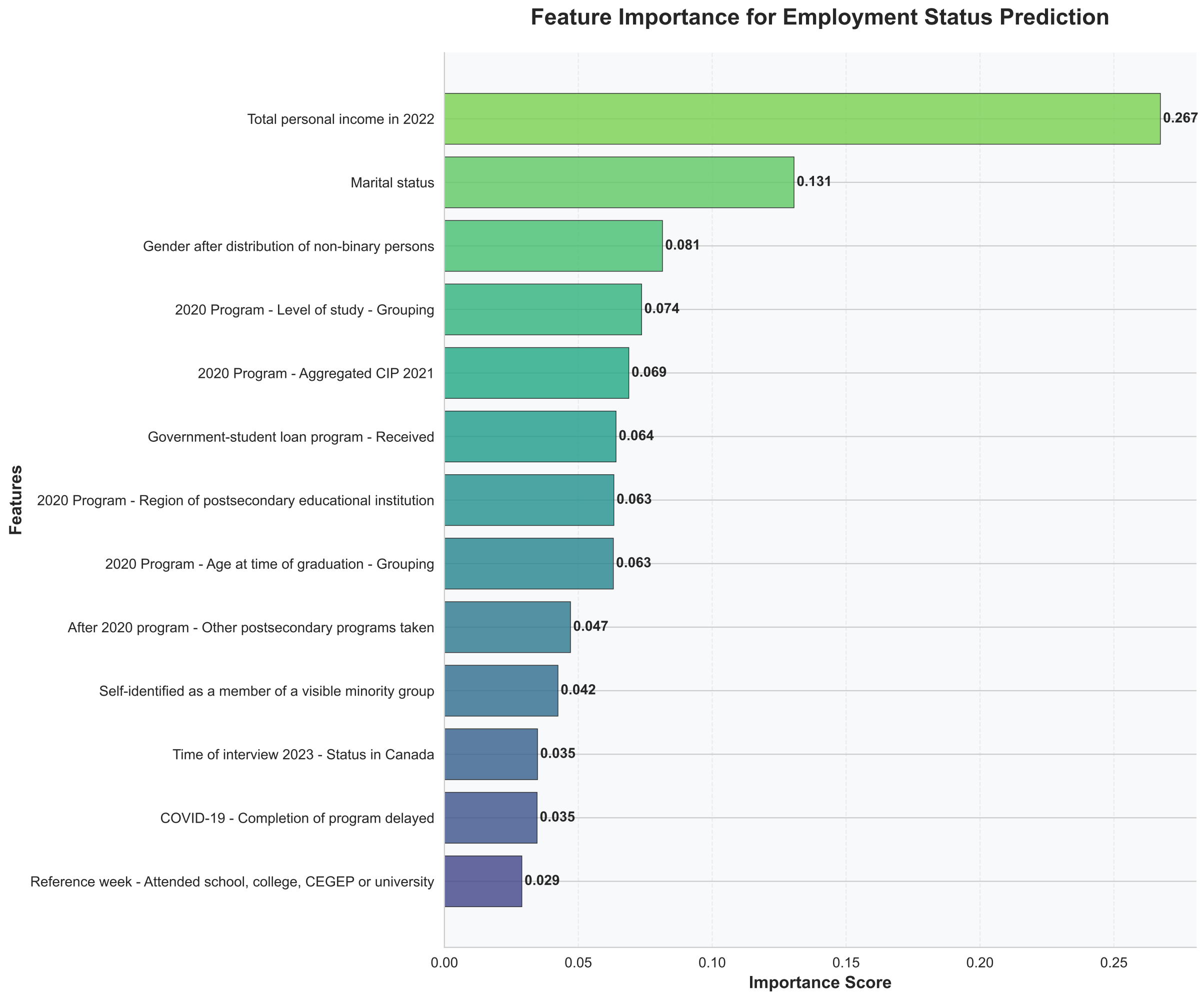



```
=== Correlation Analysis ===
```



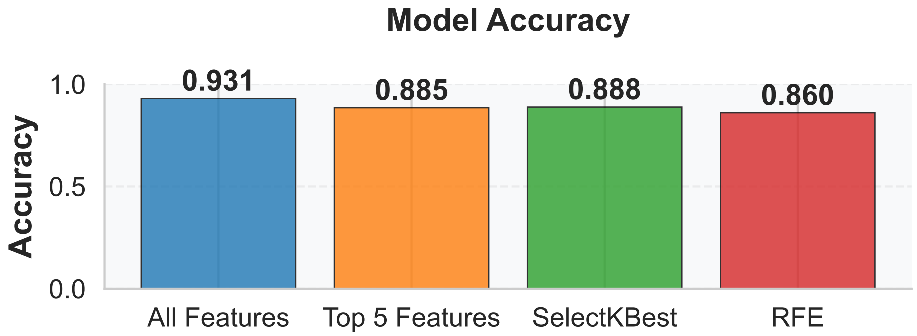

```
Using the following features for modeling: ['GENDER2', 'CERTLEVP', 'PERSINCP', 'GRADAGEP', '
```

```
=== Predictive Modeling: Employment Status Prediction ===

Removed job-related features: ['JOBINCP', 'LFCINDP', 'LFCOCCP', 'LMA6_11']
Using features: ['Gender after distribution of non-binary persons', '2020 Program - Level of
Class distribution after processing: {1.0: np.int64(5516), 2.0: np.int64(336)}
Class weights: {np.float64(1.0): np.float64(0.5304325304325305), np.float64(2.0): np.float64
After SMOTE - Class distribution: [   0 3861 3861]
1. SelectKBest Feature Selection:
Selected features: ['2020 Program - Level of study - Grouping', 'Total personal income in 20

2. Recursive Feature Elimination (RFE):
Selected features: ['Total personal income in 2022', 'Time of interview 2023 - Status in Car

3. Random Forest Feature Importance:

C:\Users\Fuxim\miniconda3\envs\quarto-env\lib\site-packages\sklearn\base.py:474: FutureWarni

`BaseEstimator._validate_data` is deprecated in 1.6 and will be removed in 1.7. Use `sklearn
```

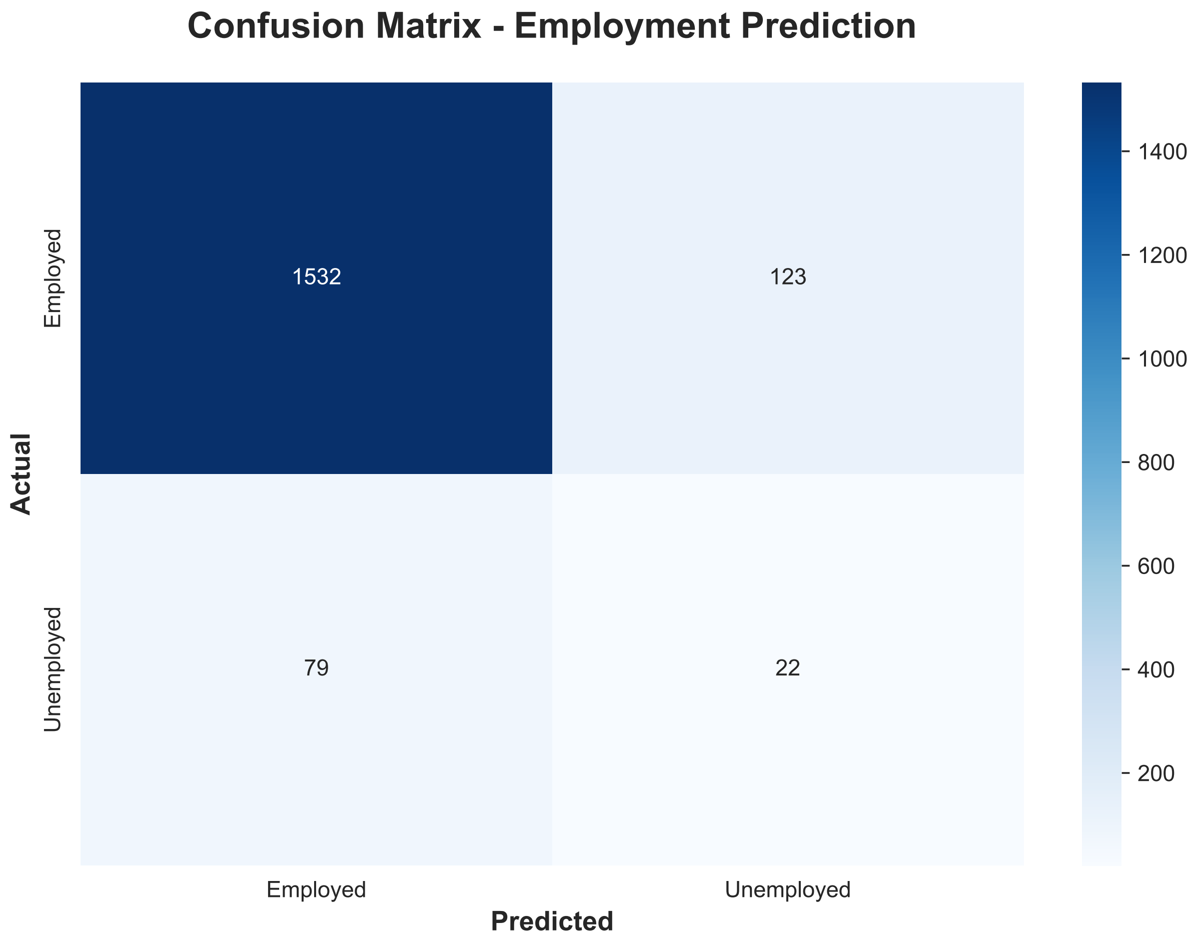



```
Top 5 features: ['Total personal income in 2022', 'Marital status', 'Gender after distributi
```

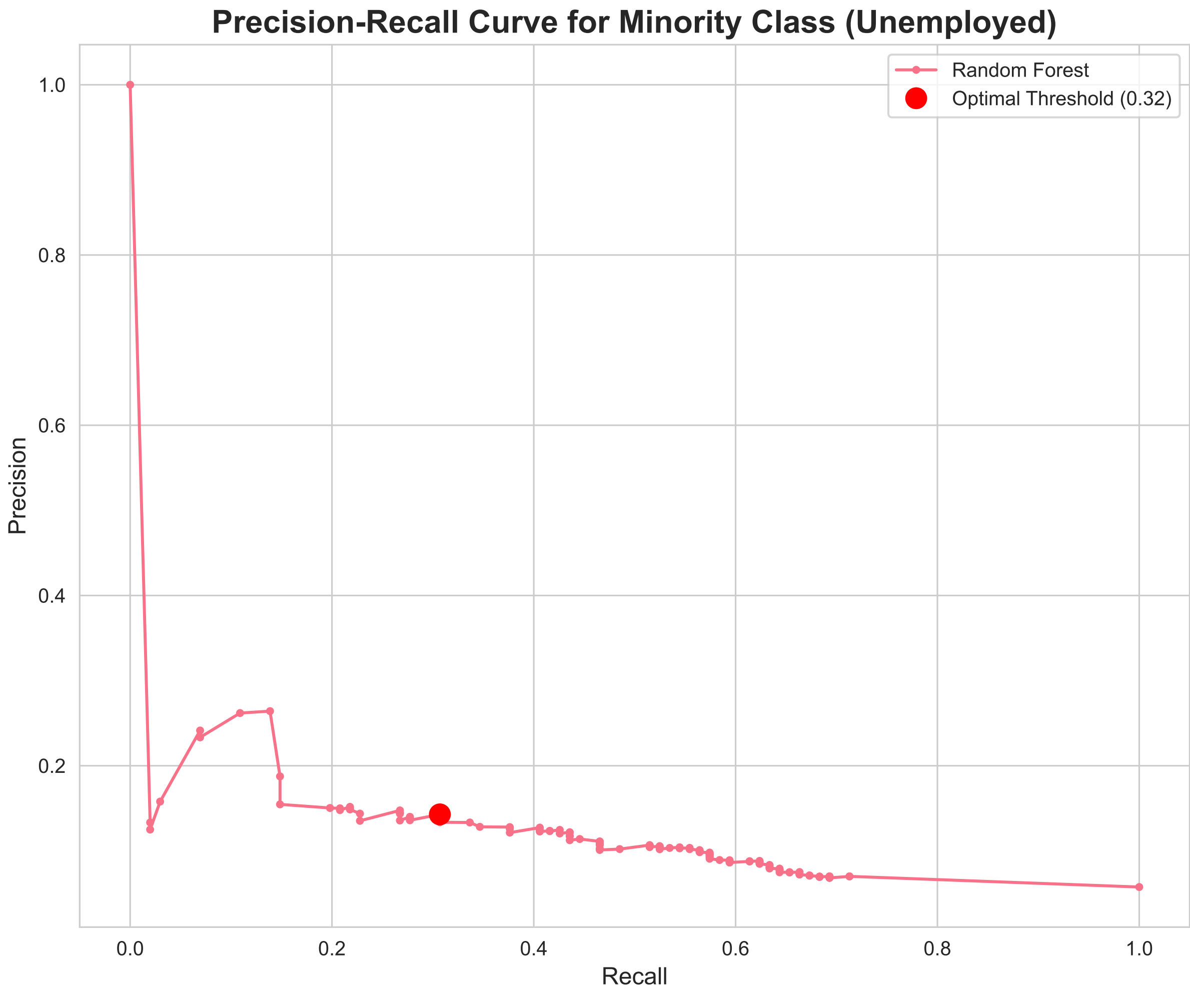
```
4. Model Performance Comparison:
All features accuracy: 0.9305239179954442
Top 5 features accuracy: 0.8849658314350797
SelectKBest features accuracy: 0.8883826879271071
RFE features accuracy: 0.8604783599088838
```




```
Classification Report - All Features:
              precision    recall  f1-score   support

         1.0       0.95      0.98      0.96      1655
         2.0       0.20      0.07      0.10       101

    accuracy                           0.93      1756
   macro avg       0.57      0.53      0.53      1756
weighted avg       0.90      0.93      0.91      1756

Classification Report - Top 5 Features:
              precision    recall  f1-score   support

         1.0       0.95      0.93      0.94      1655
         2.0       0.15      0.22      0.18       101

    accuracy                           0.88      1756
   macro avg       0.55      0.57      0.56      1756
weighted avg       0.90      0.88      0.89      1756
```

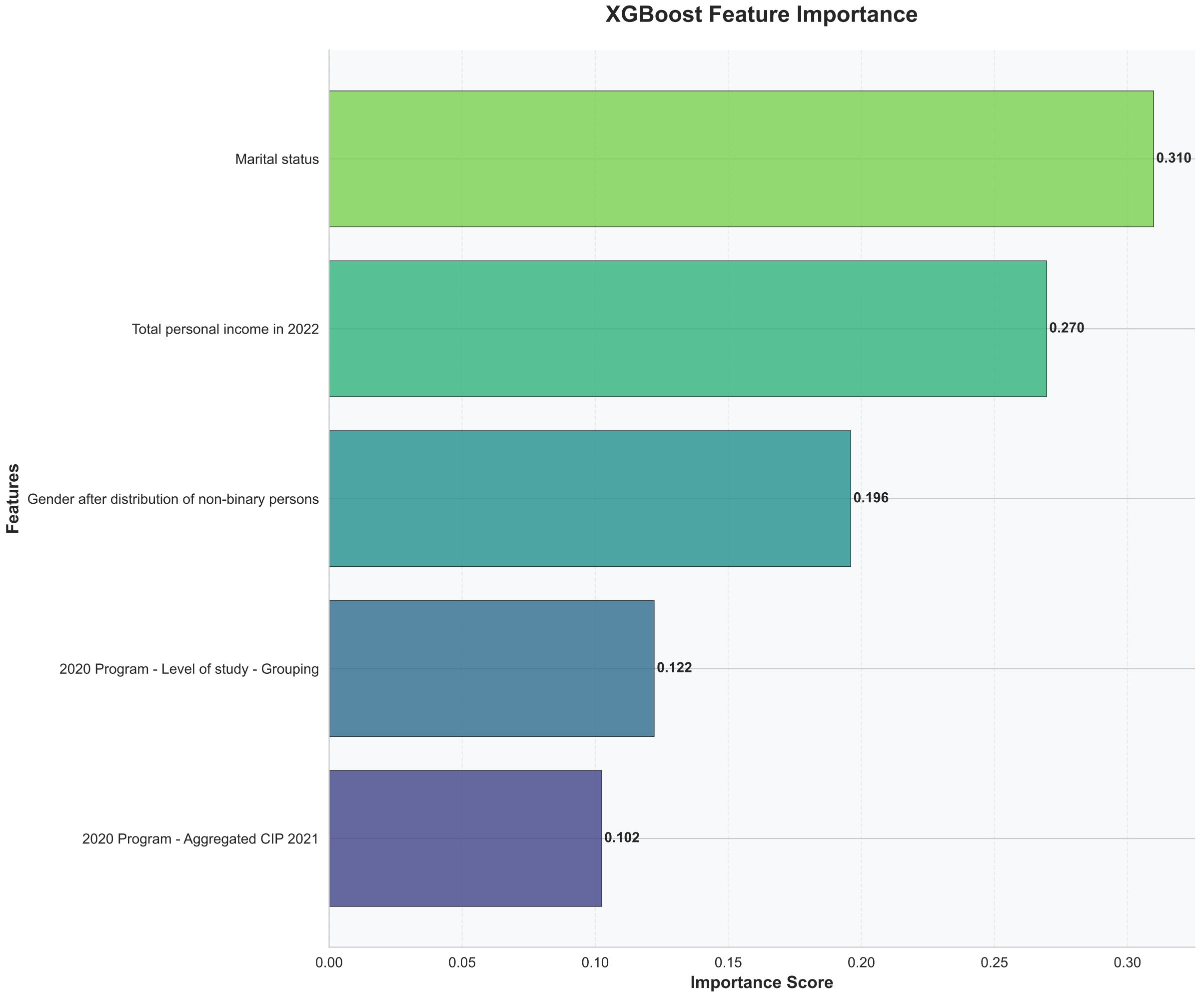


Precision-Recall AUC: 0.124

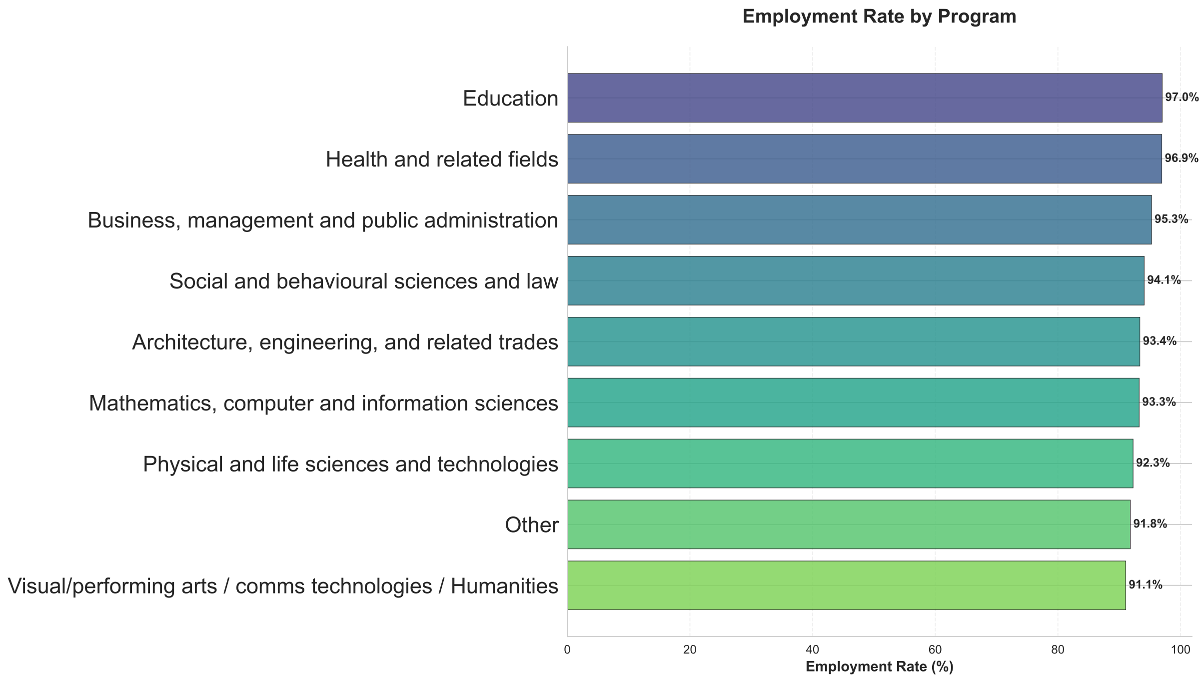



```
Optimal Threshold: 0.319
Optimal Precision: 0.143
Optimal Recall: 0.307

Classification Report with Optimal Threshold:
              precision    recall  f1-score   support

         1.0       0.95      0.89      0.92      1655
         2.0       0.14      0.31      0.19       101

    accuracy                           0.85      1756
   macro avg       0.55      0.60      0.56      1756
weighted avg       0.91      0.85      0.88      1756


6. XGBoost Model with Class Weighting:
Class ratio (majority:minority): 16.43:1
XGBoost Classification Report:
              precision    recall  f1-score   support
```

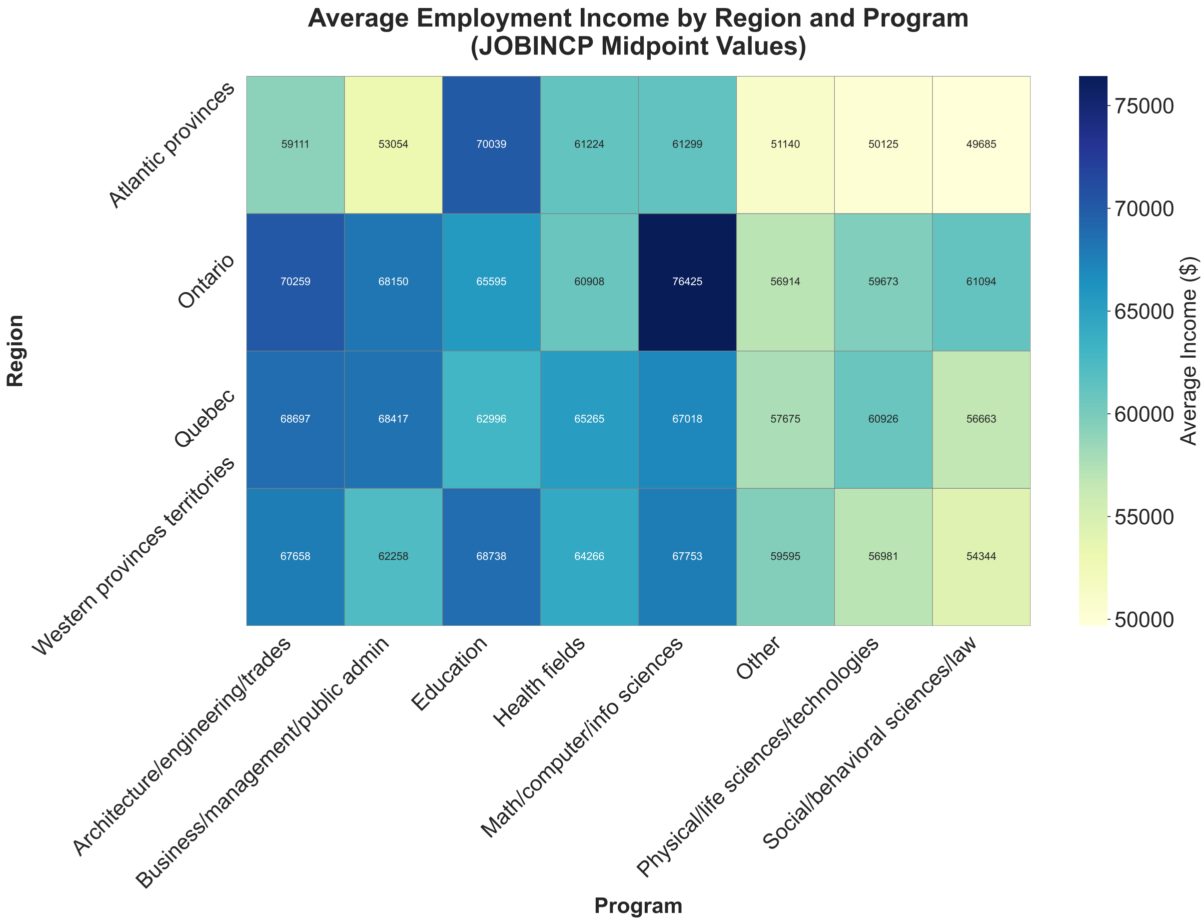
```
         1.0       0.96      0.66      0.78      1655
         2.0       0.10      0.60      0.17       101

    accuracy                           0.66      1756
   macro avg       0.53      0.63      0.48      1756
weighted avg       0.91      0.66      0.75      1756
```




```
7. Cross-Validation Results:
Cross-Validation F1 Scores: [0.91844517 0.90291254 0.91644906 0.91774194 0.92421361]
Mean CV F1 Score: 0.916 (+/- 0.014)

=== Employment Outcomes by Program ===
```




```
Programs by Employment Rate (with sufficient data):
Education: 97.0% (1167.0/1203.0 employed)
Health and related fields: 96.9% (2216.0/2286.0 employed)
Business, management and public administration: 95.3% (3465.0/3637.0 employed)
Social and behavioural sciences and law: 94.1% (1967.0/2091.0 employed)
Architecture, engineering, and related trades: 93.4% (1955.0/2094.0 employed)
Mathematics, computer and information sciences: 93.3% (829.0/889.0 employed)
Physical and life sciences and technologies: 92.3% (703.0/762.0 employed)
Other: 91.8% (807.0/879.0 employed)
Visual/performing arts / comms technologies / Humanities: 91.1% (977.0/1073.0 employed)

Note: Only 9 programs had sufficient data (>50 respondents)

=== Employment Income Heatmap (JOBINCP) ===
```




```
Summary Statistics:
Total employed individuals in analysis: 11703
Average income across all employed: $63039
Highest paying region-program combination: $76425
Lowest paying region-program combination: $49685
```

7.2 Employment Income (Linear Regression)

```python
import yaml
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.feature_selection import SelectKBest, f_regression, RFE, VarianceThreshold
from sklearn.linear_model import LinearRegression, Ridge
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
import matplotlib.ticker as mtick
import warnings
import os
```

```
# Filter out the specific warnings
warnings.filterwarnings("ignore", category=UserWarning, module="sklearn.feature_selection._u
warnings.filterwarnings("ignore", category=RuntimeWarning, module="sklearn.feature_selection

# Set professional style with a modern color palette
plt.style.use('default')
sns.set_style("whitegrid")
sns.set_palette("husl")
plt.rcParams['figure.figsize'] = (12, 8)
plt.rcParams['font.size'] = 10
plt.rcParams['axes.titlesize'] = 16
plt.rcParams['axes.titleweight'] = 'bold'
plt.rcParams['axes.labelsize'] = 12
plt.rcParams['xtick.labelsize'] = 10
plt.rcParams['ytick.labelsize'] = 10
plt.rcParams['legend.fontsize'] = 10
plt.rcParams['figure.titlesize'] = 18
plt.rcParams['figure.titleweight'] = 'bold'

# Load the YAML files with feature descriptions and response codes
def load_feature_descriptions(file_path='ngs2020_questions.yaml'):
    try:
        with open(file_path, 'r') as file:
            questions = yaml.safe_load(file)
        return questions
    except FileNotFoundError:
        print(f"Error: File '{file_path}' not found.")
        return {}
    except yaml.YAMLError as e:
        print(f"Error parsing YAML file: {e}")
        return {}

def load_response_codes(file_path='ngs2020_responses.yaml'):
    try:
        with open(file_path, 'r') as file:
            responses = yaml.safe_load(file)
        return responses
    except FileNotFoundError:
        print(f"Error: File '{file_path}' not found.")
        return {}
    except yaml.YAMLError as e:
        print(f"Error parsing YAML file: {e}")
```

```
        return {}

# Load feature descriptions and response codes
feature_descriptions = load_feature_descriptions()
response_codes = load_response_codes()

# Function to get human-readable feature names
def get_feature_name(feature_code):
    return feature_descriptions.get(feature_code, feature_code)

# Function to get human-readable response values
def get_response_value(feature_code, value):
    if feature_code in response_codes and str(value) in response_codes[feature_code]:
        return response_codes[feature_code][str(value)]
    return value

# Function to map a series to human-readable values
def map_series_to_readable(series, feature_code):
    if feature_code in response_codes:
        mapping = response_codes[feature_code]
        return series.map(lambda x: mapping.get(str(x), x))
    return series

# Function to get readable labels for plotting
def get_readable_labels(feature_code, values):
    if feature_code in response_codes:
        return [response_codes[feature_code].get(str(val), str(val)) for val in values]
    return [str(val) for val in values]

# Function to map income codes to midpoint values
def map_income_to_midpoint(income_code):
    income_mapping = {
        1: 15000,    # Less than $30,000 -> midpoint $15,000
        2: 40000,    # $30,000 to $49,999 -> midpoint $40,000
        3: 60000,    # $50,000 to $69,999 -> midpoint $60,000
        4: 80000,    # $70,000 to $89,999 -> midpoint $80,000
        5: 100000    # $90,000 or more -> approximate midpoint $100,000
    }
    return income_mapping.get(income_code, np.nan)

# Load the actual data
df = pd.read_csv('ngs2020.csv')
```

```python
# Print available columns to help debug
print("Available columns in dataset:")
print(df.columns.tolist())

# Define missing value codes based on the data documentation
missing_codes = [6, 7, 8, 9, 96, 97, 98, 99]

# Create a function to visualize missing data
def plot_missing_data(df):



    missing = df.isin(missing_codes).mean() * 100
    missing = missing[missing > 0]
    missing.sort_values(inplace=True)

    # Use human-readable feature names
    missing.index = [get_feature_name(col) for col in missing.index]

    # Create visualization
    fig, ax = plt.subplots(figsize=(12, 18))
    colors = plt.cm.viridis(np.linspace(0.2, 0.8, len(missing)))
    bars = ax.barh(missing.index, missing.values, color=colors, alpha=0.8, edgecolor='black'

    # Add value annotations on bars
    for bar in bars:
        width = bar.get_width()
        ax.text(width + 0.5, bar.get_y() + bar.get_height()/2,
                f'{width:.1f}%', ha='left', va='center', fontweight='bold', fontsize=10)

    # Styling
    ax.set_xlabel('Percentage (%)', fontweight='bold', fontsize=12)
    ax.set_ylabel('Column Name', fontweight='bold', fontsize=12)
    ax.set_title('Percentage of Missing/Special Values by Column',
                 fontsize=16, fontweight='bold', pad=20)

    # Add grid
    ax.grid(axis='x', alpha=0.3, linestyle='--')

    # Remove spines
    ax.spines[['top', 'right']].set_visible(False)
```

```
    # Add a subtle background
    ax.set_facecolor('#f8f9fa')

    plt.tight_layout()
    plt.show()

plot_missing_data(df)

# Data cleaning - replace missing codes with NaN
# Special handling for VISBMINP and GRADAGEP to preserve category 9 as a valid response
preserve_codes = {'VISBMINP': [9], 'GRADAGEP': [9]}  # Codes to keep as-is for specific vari

# for col in df.columns:
#     if df[col].dtype in ['int64', 'float64']:
#         if col in preserve_codes:
#             # For variables with preserved codes, only replace codes not in the preserve l
#             codes_to_replace = [c for c in missing_codes if c not in preserve_codes[col]]
#             df[col] = df[col].replace(codes_to_replace, np.nan)
#         else:
#             # For all other variables, replace all missing codes
#             df[col] = df[col].replace(missing_codes, np.nan)

# Data cleaning - replace missing codes with NaN
# Special handling for VISBMINP and GRADAGEP to preserve category 9 as a valid response
preserve_codes = {'VISBMINP': [9], 'GRADAGEP': [9]}  # Codes to keep as-is for specific vari

# Don't apply missing code replacement to the program column
columns_to_clean = [col for col in df.columns if col != 'PGMCIPAP']

for col in columns_to_clean:
    if df[col].dtype in ['int64', 'float64']:
        if col in preserve_codes:
            # For variables with preserved codes, only replace codes not in the preserve lis
            codes_to_replace = [c for c in missing_codes if c not in preserve_codes[col]]
            df[col] = df[col].replace(codes_to_replace, np.nan)
        else:
            # For all other variables, replace all missing codes
            df[col] = df[col].replace(missing_codes, np.nan)

# For the program column, only replace the actual missing codes (96, 97, 98, 99)
if 'PGMCIPAP' in df.columns:
    df['PGMCIPAP'] = df['PGMCIPAP'].replace([96, 97, 98, 99], np.nan)
```

```
# Map income codes to midpoint values
df['PERSINCP_midpoint'] = df['PERSINCP'].apply(map_income_to_midpoint)

# Income Distribution Analysis
def income_analysis(df):
    print("\n=== Income Distribution Analysis ===\n")

    if 'PERSINCP_midpoint' not in df.columns:
        print("Personal income data not available.")
        return

    # Filter to only employed individuals for income analysis
    income_df = df[df['LFSTATP'] == 1].copy() if 'LFSTATP' in df.columns else df.copy()

    # Create a figure for income analysis plots
    fig, axes = plt.subplots(1, 2, figsize=(8, 3))

    # Color palette
    colors = sns.color_palette("husl", 8)

    # Income distribution
    income_data = income_df['PERSINCP_midpoint'].dropna()

    print(f"{get_feature_name('PERSINCP')} Statistics:")
    print(f"Mean: ${income_data.mean():.2f}")
    print(f"Median: ${income_data.median():.2f}")
    print(f"Standard Deviation: ${income_data.std():.2f}")
    print(f"Min: ${income_data.min():.2f}")
    print(f"Max: ${income_data.max():.2f}")

    # Create histogram for income distribution
    axes[0].hist(income_data, bins=30, color=colors[0], alpha=0.8, edgecolor='black', linewi
    axes[0].set_xlabel('Income ($)', fontweight='bold', fontsize=12)
    axes[0].set_ylabel('Frequency', fontweight='bold', fontsize=12)
    # axes[0].set_title(f'{get_feature_name("PERSINCP")} Distribution', fontweight='bold', f

    # Add grid
    axes[0].grid(axis='y', alpha=0.3, linestyle='--')

    # Remove spines
    axes[0].spines[['top', 'right']].set_visible(False)
```

```
    # Income by education level
    if 'CERTLEVP' in income_df.columns:
        # Group by education level and calculate mean income
        income_by_edu = income_df.groupby('CERTLEVP')['PERSINCP_midpoint'].mean().dropna()

        # Get readable labels
        edu_labels = get_readable_labels('CERTLEVP', income_by_edu.index)

        # Create bar chart
        bars = axes[1].bar(edu_labels, income_by_edu.values, color=colors[:len(income_by_edu
                          alpha=0.8, edgecolor='black', linewidth=0.5)

        axes[1].set_title('Average Income by Education Level', fontweight='bold', fontsize=1
        axes[1].set_ylabel('Average Income ($)', fontweight='bold', fontsize=10)
        axes[1].tick_params(axis='x', rotation=20)
        axes[1].set_xticklabels(["College","Bachelor's","Master's / Doctorate"])

        # Add value labels on top of bars
        for bar in bars:
            height = bar.get_height()
            axes[1].text(bar.get_x() + bar.get_width()/2., height + 500,
                        f'${height:.0f}', ha='center', va='bottom', fontweight='bold')

        # Add grid
        axes[1].grid(axis='y', alpha=0.3, linestyle='--')

        # Remove spines
        axes[1].spines[['top', 'right']].set_visible(False)
    else:
        axes[1].set_visible(False)
        print("Education level data (CERTLEVP) not available for income analysis.")

    # Add a background color to the figure
    fig.patch.set_facecolor('#f8f9fa')

    plt.tight_layout()
    plt.show()

income_analysis(df)

# Correlation Analysis with Income Focus
def correlation_analysis(df):
```

```
print("\n=== Correlation Analysis ===\n")

# Select columns that might have meaningful correlations with income
corr_cols = [
    'GRADAGEP',
    'PERSINCP_midpoint',
    'JOBINCP',
    'STULOANS',
    'CERTLEVP',
]

# Add additional columns if they exist
optional_cols = ['LFCINDP', 'LFCOCCP', 'COV_010', 'GENDER2', 'VISBMINP', 'CTZSHIPP']
for col in optional_cols:
    if col in df.columns:
        corr_cols.append(col)

# Filter to only include columns that exist in the dataset
corr_cols = [col for col in corr_cols if col in df.columns]

if len(corr_cols) < 2:
    print("Not enough columns for correlation analysis.")
    return

corr_df = df[corr_cols].copy()

# Filter out missing codes
for col in corr_cols:
    corr_df = corr_df[~corr_df[col].isin(missing_codes)]

# Compute correlation matrix
corr_matrix = corr_df.corr()

# Get human-readable labels
human_labels = [get_feature_name(col) for col in corr_cols]

# Plot heatmap
plt.figure(figsize=(12, 10))

# Create a mask for the upper triangle
mask = np.triu(np.ones_like(corr_matrix, dtype=bool))
```

```
    # Create heatmap with mask
    heatmap = sns.heatmap(
        corr_matrix,
        annot=True,
        cmap='RdBu_r',
        center=0,
        fmt=".2f",
        square=True,
        mask=mask,
        cbar_kws={"shrink": 0.8},
        annot_kws={"size": 11, "weight": "bold"},
        linewidths=0.5,
        linecolor='white'
    )

    # Set title
    plt.title('Correlation Matrix of Key Variables (Income Focus)', fontsize=16, fontweight=

    # Set x-axis labels with rotation
    heatmap.set_xticklabels(human_labels, rotation=30, ha='right', fontsize=18)

    # Set y-axis labels with proper rotation and alignment
    heatmap.set_yticklabels(human_labels, rotation=0, va='center', fontsize=18)

    # Add a background
    plt.gca().set_facecolor('#f8f9fa')

    plt.tight_layout()
    plt.show()

correlation_analysis(df)

# Define potential features for income prediction modeling
potential_features = [
    'GENDER2', 'CERTLEVP', 'GRADAGEP', 'VISBMINP',
    'CTZSHIPP', 'MS_P01', 'REG_INST', 'EDU_010',
    'PGMCIPAP', 'STULOANS', 'JOBINCP'
]

# Add optional features if they exist in the dataset
optional_features = ['LFCINDP', 'LFCOCCP', 'LMA6_11', 'COV_010', 'LMA_010', 'LMA_020', 'LMA_
for feature in optional_features:
```

```
    if feature in df.columns:
        potential_features.append(feature)

# Filter to only include columns that exist in the dataset
potential_features = [col for col in potential_features if col in df.columns]

print(f"Using the following features for modeling: {potential_features}")

# Predictive Modeling with Feature Selection for Income
def predict_income(df, features):
    print("\n=== Predictive Modeling: Income Prediction ===\n")

    if 'PERSINCP_midpoint' not in df.columns:
        print("Income data (PERSINCP_midpoint) not available for modeling.")
        return

    # Filter to only employed individuals for income prediction
    if 'LFSTATP' in df.columns:
        employed_df = df[df['LFSTATP'] == 1].copy()
    else:
        employed_df = df.copy()

    # Remove job-related features that might have high missing rates
    job_features_to_remove = ['JOBINCP', 'LFCINDP', 'LFCOCCP', 'LMA6_11']
    features = [f for f in features if f not in job_features_to_remove]
    print(f"Removed job-related features: {job_features_to_remove}")
    print(f"Using features: {[get_feature_name(f) for f in features]}")

    # Prepare data with potential features
    model_df = employed_df[features + ['PERSINCP_midpoint']].copy()

    # Replace missing codes with NaN
    for col in model_df.columns:
        if model_df[col].dtype in ['int64', 'float64']:
            if col in preserve_codes:
                codes_to_replace = [c for c in missing_codes if c not in preserve_codes[col]
                model_df[col] = model_df[col].replace(codes_to_replace, np.nan)
            else:
                model_df[col] = model_df[col].replace(missing_codes, np.nan)

    # Drop rows with missing values
    model_df = model_df.dropna()
```

```
# Check data size
if len(model_df) < 100:
    print(f"Not enough data for modeling. Only {len(model_df)} samples available.")
    return

# Convert categorical variables to numerical
le = LabelEncoder()
for col in features:
    if model_df[col].dtype == 'object':
        model_df[col] = le.fit_transform(model_df[col])

# Split data
X = model_df.drop('PERSINCP_midpoint', axis=1)
y = model_df['PERSINCP_midpoint']
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42
)

# Remove constant features
selector = VarianceThreshold()
X_train_clean = selector.fit_transform(X_train)
X_test_clean = selector.transform(X_test)

# Get the feature names after removing constant features
selected_features = X.columns[selector.get_support()]
X_train = pd.DataFrame(X_train_clean, columns=selected_features)
X_test = pd.DataFrame(X_test_clean, columns=selected_features)

if len(selected_features) == 0:
    print("No features remaining after variance threshold. Cannot proceed with modeling.
    return

# Feature Selection Methods
# Method 1: SelectKBest with F-regression
print("1. SelectKBest Feature Selection:")
k = min(5, len(selected_features))
selector_kbest = SelectKBest(score_func=f_regression, k=k)
X_kbest = selector_kbest.fit_transform(X_train, y_train)
selected_features_kbest = selected_features[selector_kbest.get_support()]
selected_features_kbest_desc = [get_feature_name(feat) for feat in selected_features_kbe
print(f"Selected features: {selected_features_kbest_desc}")
```

```
# Method 2: Recursive Feature Elimination (RFE)
print("\n2. Recursive Feature Elimination (RFE):")
estimator = LinearRegression()
n_features = min(5, len(selected_features))
selector_rfe = RFE(estimator, n_features_to_select=n_features, step=1)
X_rfe = selector_rfe.fit_transform(X_train, y_train)
selected_features_rfe = selected_features[selector_rfe.get_support()]
selected_features_rfe_desc = [get_feature_name(feat) for feat in selected_features_rfe]
print(f"Selected features: {selected_features_rfe_desc}")

# Method 3: Feature Importance from Random Forest
print("\n3. Random Forest Feature Importance:")
rf = RandomForestRegressor(random_state=42)
rf.fit(X_train, y_train)

# Plot feature importance
importance = pd.Series(rf.feature_importances_, index=selected_features)
importance.index = [get_feature_name(feat) for feat in importance.index]
importance = importance.sort_values(ascending=True)

# Create a horizontal bar chart for feature importance
plt.figure(figsize=(12, 10))
colors = plt.cm.viridis(np.linspace(0.2, 0.8, len(importance)))
bars = plt.barh(importance.index, importance.values, color=colors, alpha=0.8, edgecolor=
plt.tick_params(axis='y', labelsize=18)


# Add value annotations on bars
for bar in bars:
    width = bar.get_width()
    plt.text(width + 0.001, bar.get_y() + bar.get_height()/2,
            f'{width:.3f}', ha='left', va='center', fontweight='bold', fontsize=10)

# Styling
plt.xlabel('Importance Score', fontweight='bold', fontsize=12)
plt.ylabel('Features', fontweight='bold', fontsize=12)
plt.title('Feature Importance for Income Prediction', fontsize=16, fontweight='bold', pa

# Add grid
plt.grid(axis='x', alpha=0.3, linestyle='--')

# Remove spines
```

```python
plt.gca().spines[['top', 'right']].set_visible(False)

# Add a background
plt.gca().set_facecolor('#f8f9fa')

plt.tight_layout()
plt.show()

# Select top 5 features based on importance
top_features = importance.nlargest(min(5, len(importance))).index.tolist()
print(f"Top 5 features: {top_features}")

# Compare performance with and without feature selection
print("\n4. Model Performance Comparison:")

# Baseline model (all features)
model_all = RandomForestRegressor(random_state=42)
model_all.fit(X_train, y_train)
y_pred_all = model_all.predict(X_test)
rmse_all = np.sqrt(mean_squared_error(y_test, y_pred_all))
r2_all = r2_score(y_test, y_pred_all)
print(f"All features RMSE: ${rmse_all:.2f}, R²: {r2_all:.3f}")

# Model with top 5 features from RF importance
top_feature_codes = [feat for feat in selected_features if get_feature_name(feat) in top
X_train_top = X_train[top_feature_codes]
X_test_top = X_test[top_feature_codes]

model_top = RandomForestRegressor(random_state=42)
model_top.fit(X_train_top, y_train)
y_pred_top = model_top.predict(X_test_top)
rmse_top = np.sqrt(mean_squared_error(y_test, y_pred_top))
r2_top = r2_score(y_test, y_pred_top)
print(f"Top 5 features RMSE: ${rmse_top:.2f}, R²: {r2_top:.3f}")

# Model with SelectKBest features
X_train_kbest = X_train[selected_features_kbest]
X_test_kbest = X_test[selected_features_kbest]

model_kbest = RandomForestRegressor(random_state=42)
model_kbest.fit(X_train_kbest, y_train)
y_pred_kbest = model_kbest.predict(X_test_kbest)
```

```
rmse_kbest = np.sqrt(mean_squared_error(y_test, y_pred_kbest))
r2_kbest = r2_score(y_test, y_pred_kbest)
print(f"SelectKBest features RMSE: ${rmse_kbest:.2f}, R²: {r2_kbest:.3f}")

# Model with RFE features
X_train_rfe = X_train[selected_features_rfe]
X_test_rfe = X_test[selected_features_rfe]

model_rfe = RandomForestRegressor(random_state=42)
model_rfe.fit(X_train_rfe, y_train)
y_pred_rfe = model_rfe.predict(X_test_rfe)
rmse_rfe = np.sqrt(mean_squared_error(y_test, y_pred_rfe))
r2_rfe = r2_score(y_test, y_pred_rfe)
print(f"RFE features RMSE: ${rmse_rfe:.2f}, R²: {r2_rfe:.3f}")

# Create a comparison chart for R² scores
methods = ['All Features', 'Top 5 Features', 'SelectKBest', 'RFE']
r2_scores = [r2_all, r2_top, r2_kbest, r2_rfe]

# Create a comparison bar chart
plt.figure(figsize=(10, 6))
colors = ['#1f77b4', '#ff7f0e', '#2ca02c', '#d62728']
bars = plt.bar(methods, r2_scores, color=colors, alpha=0.8, edgecolor='black', linewidth

# Add value labels on top of bars
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2., height + 0.01,
            f'{height:.3f}', ha='center', va='bottom', fontweight='bold', fontsize=11)

# Styling
plt.ylabel('R² Score', fontweight='bold', fontsize=12)
plt.title('Model Performance (R²) by Feature Selection Method', fontsize=16, fontweight=
plt.ylim(0, 1)

# Add grid
plt.grid(axis='y', alpha=0.3, linestyle='--')

# Remove spines
plt.gca().spines[['top', 'right']].set_visible(False)

# Add a background
```

```
    plt.gca().set_facecolor('#f8f9fa')

    plt.tight_layout()
    plt.show()

    # Create actual vs predicted plot for the best model
    best_model = model_top  # Using top features model
    y_pred_best = best_model.predict(X_test_top)

    plt.figure(figsize=(10, 6))
    plt.scatter(y_test, y_pred_best, alpha=0.5)
    plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--', lw=2)
    plt.xlabel('Actual Income ($)', fontweight='bold')
    plt.ylabel('Predicted Income ($)', fontweight='bold')
    plt.title('Actual vs Predicted Income', fontsize=16, fontweight='bold', pad=20)

    # Add grid
    plt.grid(alpha=0.3, linestyle='--')

    # Remove spines
    plt.gca().spines[['top', 'right']].set_visible(False)

    plt.tight_layout()
    plt.show()

# Run predictive modeling with the fixed function
predict_income(df, potential_features)

# Additional analysis: Income by program
# Additional analysis: Income by program
def income_by_program(df):
    print("\n=== Income Outcomes by Program ===\n")

    if 'PGMCIPAP' not in df.columns or 'PERSINCP_midpoint' not in df.columns:
        print("Program or income data not available.")
        return

    # Filter to only employed individuals
    income_df = df[df['LFSTATP'] == 1].copy() if 'LFSTATP' in df.columns else df.copy()

    # Create a mapping dictionary for program codes to names
    program_mapping = {
```

```
        1: "Education",
        2: "Visual/performing arts/comms/humanities",
        4: "Social/behavioral sciences/law",
        5: "Business/management/public admin",
        6: "Physical/life sciences/technologies",
        7: "Math/computer/info sciences",
        8: "Architecture/engineering/trades",
        9: "Health fields",
        10: "Other",
        99: "Not stated"
    }

    # Group by program and calculate mean income
    program_income = income_df.groupby('PGMCIPAP')['PERSINCP_midpoint'].agg(['mean', 'count'

    # Filter out "Not stated" (code 99)
    program_income = program_income[program_income.index != 99]

    # Separate programs with sufficient data (>50) and insufficient data (<=50)
    sufficient_programs = program_income[program_income['count'] > 50]
    insufficient_programs = program_income[program_income['count'] <= 50]

    # Visualize only programs with sufficient data
    if len(sufficient_programs) > 0:
        # Sort by mean income
        sufficient_programs = sufficient_programs.sort_values('mean', ascending=False)

        # Create visualization
        fig, ax = plt.subplots(figsize=(8, 4))  # Increased size to accommodate more categor

        # Get program names using our mapping
        program_labels = [program_mapping.get(pid, f"Program {pid}") for pid in sufficient_p

        # Create bar chart with vertical bars
        colors = plt.cm.viridis(np.linspace(0.2, 0.8, len(sufficient_programs)))
        bars = ax.bar(range(len(sufficient_programs)), sufficient_programs['mean'],
                      color=colors, alpha=0.8, edgecolor='black', linewidth=0.5)

        ax.set_xticks(range(len(sufficient_programs)))
        ax.set_xticklabels(program_labels, fontsize=12, rotation=30, ha='right')
        ax.set_ylabel('Average Income ($)', fontweight='bold')
        ax.set_title('Average Income by Program', fontsize=16, fontweight='bold', pad=20)
```

```
    # Add value labels
    for i, bar in enumerate(bars):
        height = bar.get_height()
        ax.text(bar.get_x() + bar.get_width()/2, height + 500,
                f'${height:.0f}', ha='center', va='bottom', fontweight='bold')

    # Add grid
    ax.grid(axis='y', alpha=0.3, linestyle='--')

    # Remove spines
    ax.spines[['top', 'right']].set_visible(False)

    plt.tight_layout()
    plt.show()

    # Print the results with more information
    print("Programs by Average Income (with sufficient data, n > 50):")
    for pid, row in sufficient_programs.iterrows():
        program_name = program_mapping.get(pid, f"Program {pid}")
        avg_income = row['mean']
        count = row['count']

        print(f"{program_name}: ${avg_income:.0f} (n={count})")

    # Provide additional context
    print(f"\nNote: {len(sufficient_programs)} programs had sufficient data (>50 respond
else:
    print("No programs had sufficient data (>50 respondents) for visualization.")

# Print information for programs with insufficient data
if len(insufficient_programs) > 0:
    print(f"\nPrograms with Limited Data (n <= 50):")

    # Sort by count (descending) to show programs with the most data first
    insufficient_programs = insufficient_programs.sort_values('count', ascending=False)

    for pid, row in insufficient_programs.iterrows():
        program_name = program_mapping.get(pid, f"Program {pid}")
        avg_income = row['mean']
        count = row['count']

        print(f"{program_name}: ${avg_income:.0f} (n={count})")
```

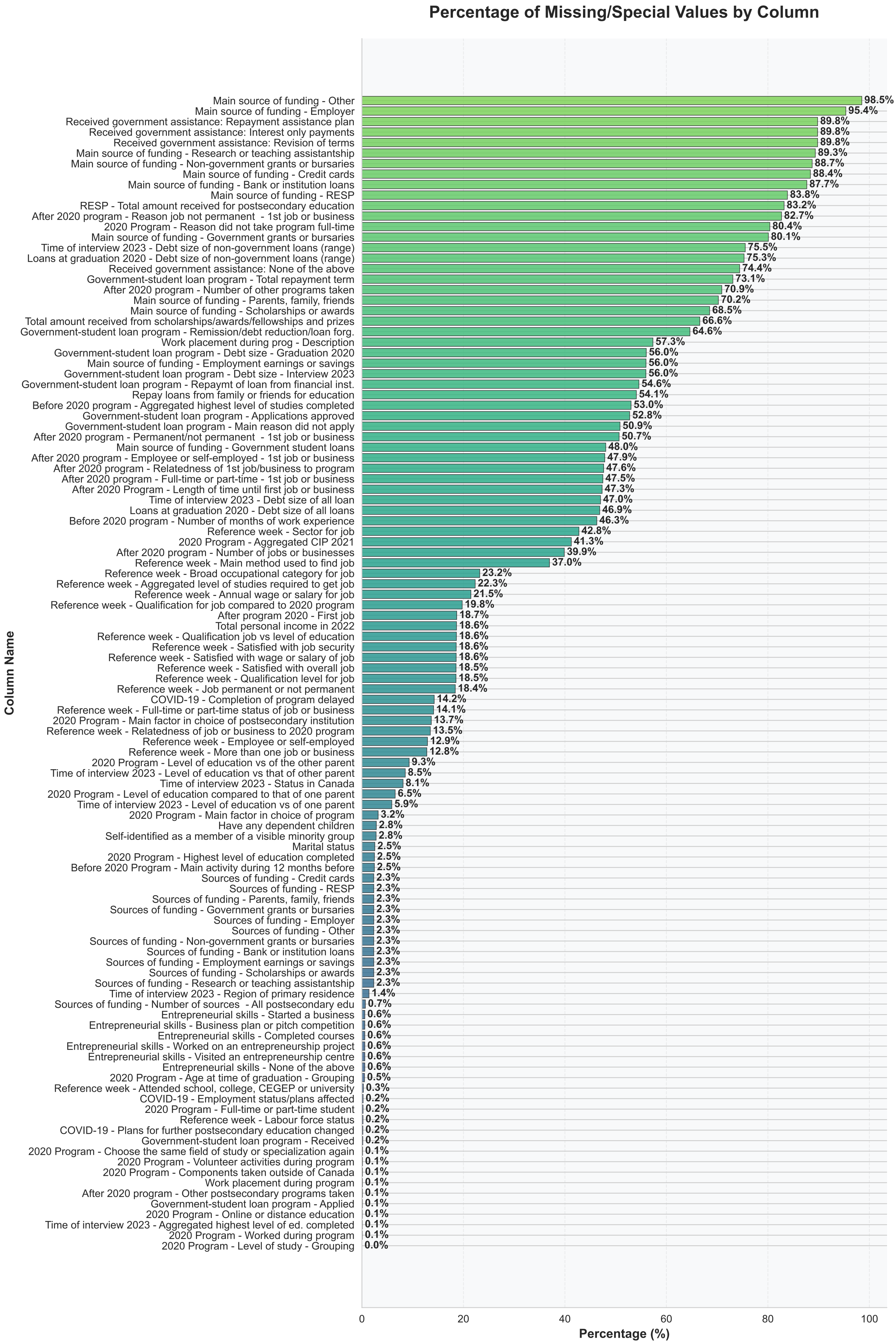
```
        print(f"\nNote: {len(insufficient_programs)} programs had limited data (<=50 respond
    else:
        print("\nNo programs had limited data (<=50 respondents).")

# Run the program analysis
income_by_program(df)

import numpy as np
import matplotlib.pyplot as plt
from matplotlib.ticker import FuncFormatter

import numpy as np
import matplotlib.pyplot as plt
from matplotlib.ticker import FuncFormatter

import numpy as np
import matplotlib.pyplot as plt
from matplotlib.ticker import FuncFormatter

def income_by_program_tier(df):
    print("\n=== Income by Program Tier ===\n")

    if 'PGMCIPAP' not in df.columns or 'PERSINCP_midpoint' not in df.columns:
        print("Program or income data not available.")
        return

    # Filter to only employed individuals
    income_df = df[df['LFSTATP'] == 1].copy() if 'LFSTATP' in df.columns else df.copy()

    # Define program tiers
    program_tiers = {
        'Tier 1': [1, 7, 9],  # Education, Math/Computer Science, Health
        'Tier 2': [5, 8],      # Business/Management, Engineering/Trades
        'Tier 3': [2, 3, 4, 6] # Arts/Humanities, Social Sciences, Life Sciences
    }

    # Map programs to tiers
    def map_to_tier(program_code):
        for tier, codes in program_tiers.items():
            if program_code in codes:
                return tier
        return 'Other/Unknown'
```

```python
income_df['Program_Tier'] = income_df['PGMCIPAP'].apply(map_to_tier)

# Filter out 'Other/Unknown' and keep only relevant tiers
tier_df = income_df[income_df['Program_Tier'] != 'Other/Unknown']

# Set professional style
plt.style.use('default')
plt.rcParams['font.family'] = 'DejaVu Sans'
plt.rcParams['axes.facecolor'] = 'white'
plt.rcParams['grid.color'] = '#E0E0E0'

# Create a single, focused visualization
fig, ax = plt.subplots(figsize=(10, 6))

# Prepare data for boxplot
box_data = []
tier_labels = []
tier_colors = ['#4C72B0', '#55A868', '#C44E52']  # Blue, Green, Red

for i, tier in enumerate(['Tier 1', 'Tier 2', 'Tier 3']):
    tier_data = tier_df[tier_df['Program_Tier'] == tier]['PERSINCP_midpoint'].dropna()
    box_data.append(tier_data)
    tier_labels.append(f"{tier}\n(n={len(tier_data):,})")

# Create boxplot with updated parameter name
box_plot = ax.boxplot(box_data, patch_artist=True)

# Customize box colors
for i, patch in enumerate(box_plot['boxes']):
    patch.set_facecolor(tier_colors[i])
    patch.set_alpha(0.7)

# Customize other elements
for element in ['whiskers', 'caps']:
    plt.setp(box_plot[element], color='black', linewidth=1)

for median in box_plot['medians']:
    median.set_color('black')
    median.set_linewidth(2)

# Set x-tick labels separately to avoid deprecation warning
ax.set_xticks([1, 2, 3])
```

```
ax.set_xticklabels(tier_labels)

# Customize labels and title
ax.set_title('Income Distribution by Program Tier', fontsize=16, fontweight='bold', pad=
ax.set_xlabel('Program Tier', fontweight='bold', fontsize=12)
ax.set_ylabel('Annual Income ($)', fontweight='bold', fontsize=12)

# Format y-axis with dollar signs
def currency_formatter(x, pos):
    return f'${x:,.0f}'

ax.yaxis.set_major_formatter(FuncFormatter(currency_formatter))

# Remove spines and adjust grid
ax.spines[['top', 'right']].set_visible(False)
ax.grid(axis='y', alpha=0.3, linestyle='--')

# Add mean markers
for i, tier in enumerate(['Tier 1', 'Tier 2', 'Tier 3']):
    mean_income = tier_df[tier_df['Program_Tier'] == tier]['PERSINCP_midpoint'].mean()
    ax.plot(i+1, mean_income, 'o', color='yellow', markersize=8, markeredgecolor='black'
            label='Mean' if i == 0 else "")

# Add legend for mean marker
ax.legend(loc='upper right', frameon=True, fancybox=True, shadow=True)

plt.tight_layout()
plt.show()

# Print detailed summary statistics
print("Detailed Income Statistics by Program Tier:")
print("-" * 50)
for tier in ['Tier 1', 'Tier 2', 'Tier 3']:
    tier_data = tier_df[tier_df['Program_Tier'] == tier]['PERSINCP_midpoint']
    print(f"{tier}:")
    print(f"  Count: {len(tier_data):,}")
    print(f"  Mean: ${tier_data.mean():,.0f}")
    print(f"  Median: ${tier_data.median():,.0f}")
    print(f"  Std Dev: ${tier_data.std():,.0f}")
    print(f"  25th Percentile: ${tier_data.quantile(0.25):,.0f}")
    print(f"  75th Percentile: ${tier_data.quantile(0.75):,.0f}")
    print()
```

```
    # Add a clear interpretation of the results
    print("\n=== Key Findings ===")
    tier1_data = tier_df[tier_df['Program_Tier'] == 'Tier 1']['PERSINCP_midpoint']
    tier2_data = tier_df[tier_df['Program_Tier'] == 'Tier 2']['PERSINCP_midpoint']
    tier3_data = tier_df[tier_df['Program_Tier'] == 'Tier 3']['PERSINCP_midpoint']

    print(f"1. Tier 1 graduates earn ${tier1_data.mean():,.0f} on average, which is " +
          f"${tier1_data.mean() - tier2_data.mean():,.0f} more than Tier 2 and " +
          f"${tier1_data.mean() - tier3_data.mean():,.0f} more than Tier 3 graduates.")

    print(f"2. Tier 3 graduates have the lowest median income (${tier3_data.median():,.0f})
          f"and the highest income variability (standard deviation of ${tier3_data.std():,.(

    print(f"3. 25% of Tier 3 graduates earn less than ${tier3_data.quantile(0.25):,.0f}, " +
          "indicating more financial instability in these fields.")

    print("4. Despite similar median incomes, Tier 1 graduates have higher earning potential
          f"with 25% earning over ${tier1_data.quantile(0.75):,.0f} compared to " +
          f"${tier2_data.quantile(0.75):,.0f} for Tier 2 graduates.")

# Call the function after the existing income_by_program function
income_by_program_tier(df)
```

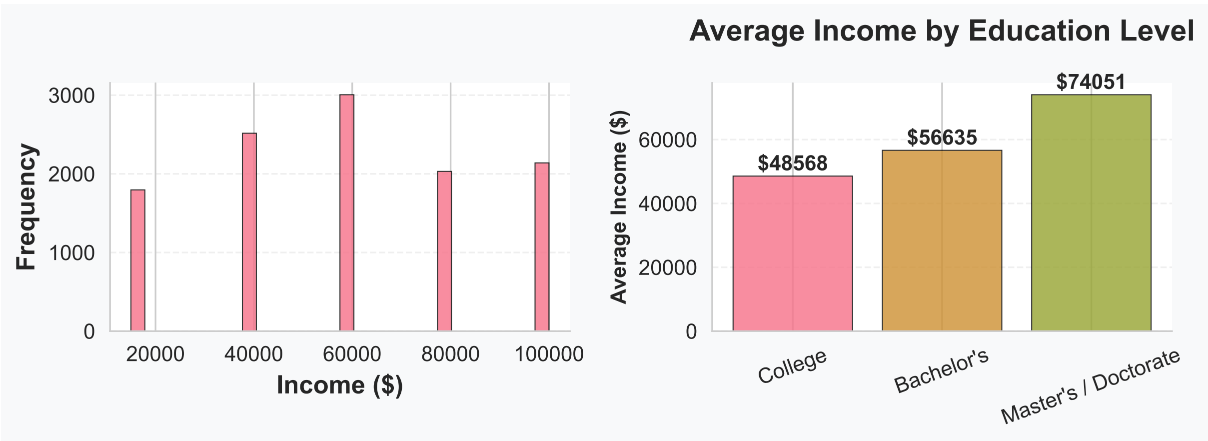
```
Available columns in dataset:
['PUMFID', 'CERTLEVP', 'REG_INST', 'REG_RESP', 'PGMCIPAP', 'PGM_P034', 'PGM_P036', 'PGM_P10(
```



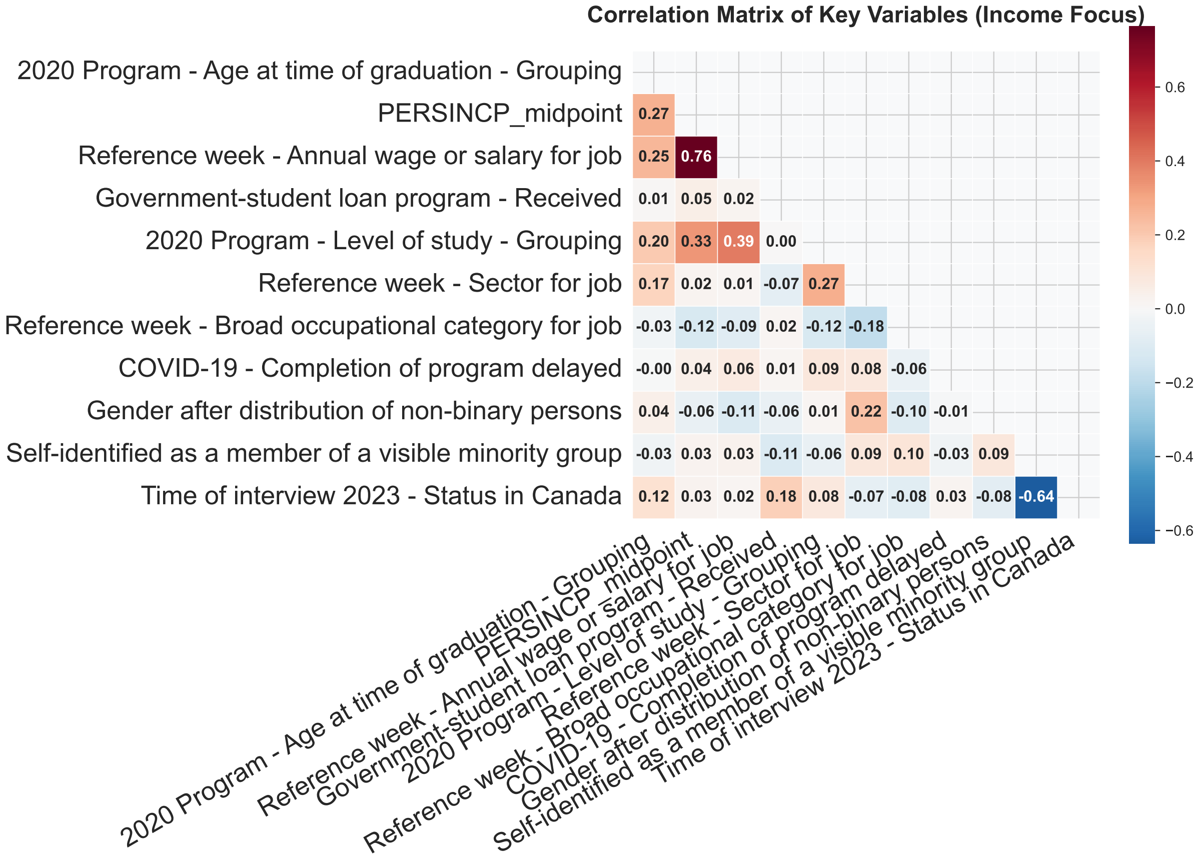

```
=== Income Distribution Analysis ===
```

```
Total personal income in 2022 Statistics:
Mean: $59568.25
Median: $60000.00
Standard Deviation: $27797.41
Min: $15000.00
Max: $100000.00
```

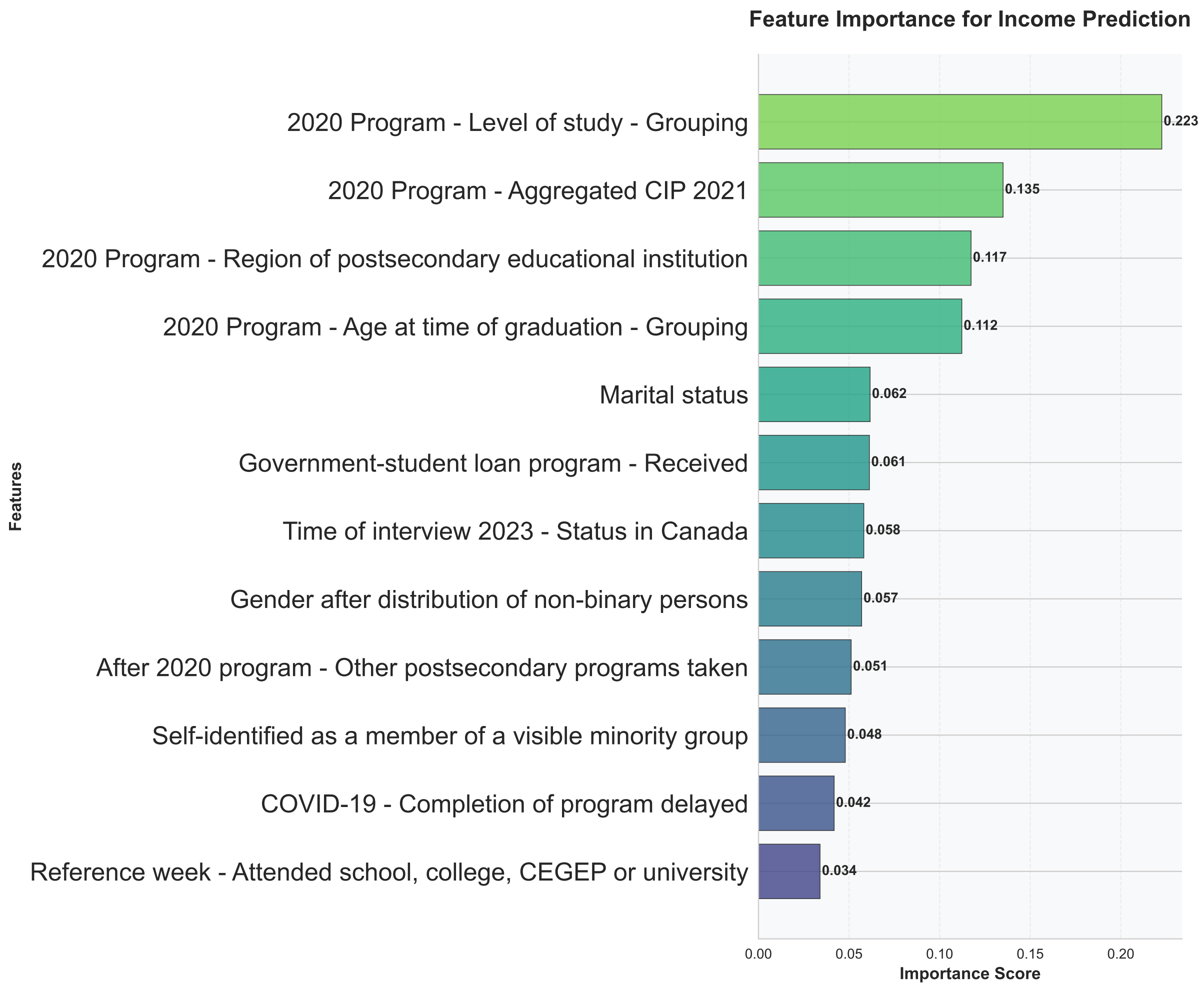
```
C:\Users\Fuxim\AppData\Local\Temp\ipykernel_38356\2592278665.py:187: PerformanceWarning:

DataFrame is highly fragmented.  This is usually the result of calling `frame.insert` many t

C:\Users\Fuxim\AppData\Local\Temp\ipykernel_38356\2592278665.py:243: UserWarning:

set_ticklabels() should only be used with a fixed number of ticks, i.e. after set_ticks() or
```



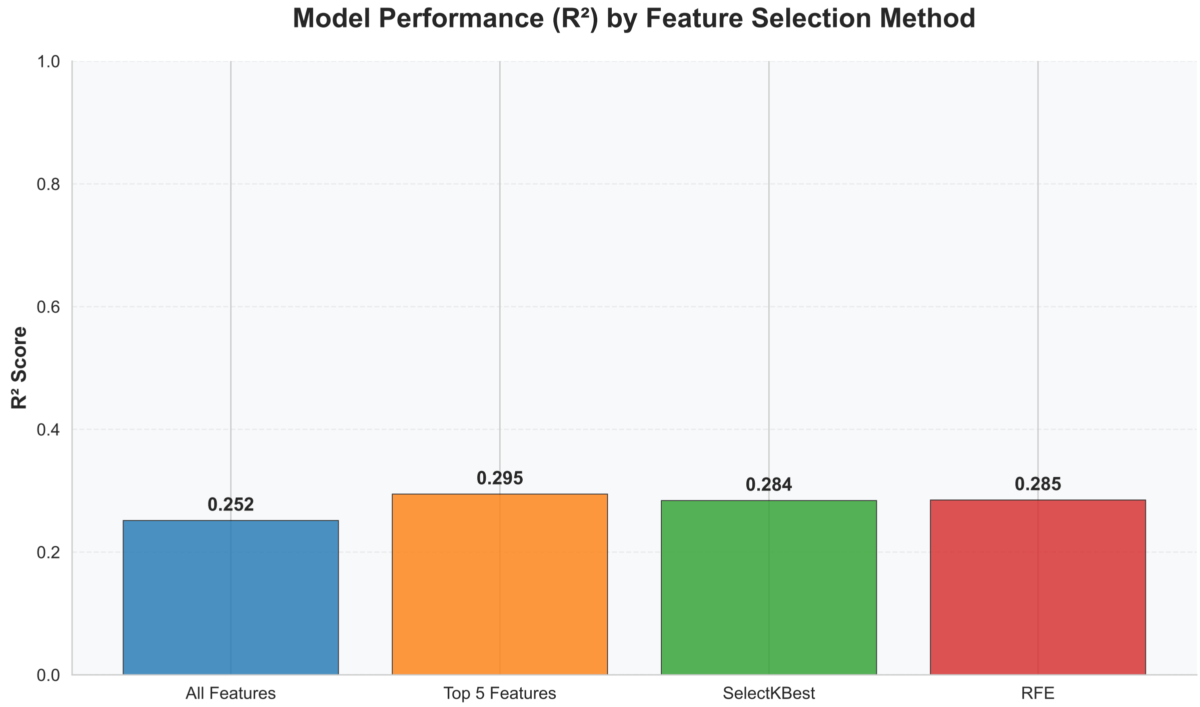

```
=== Correlation Analysis ===
```

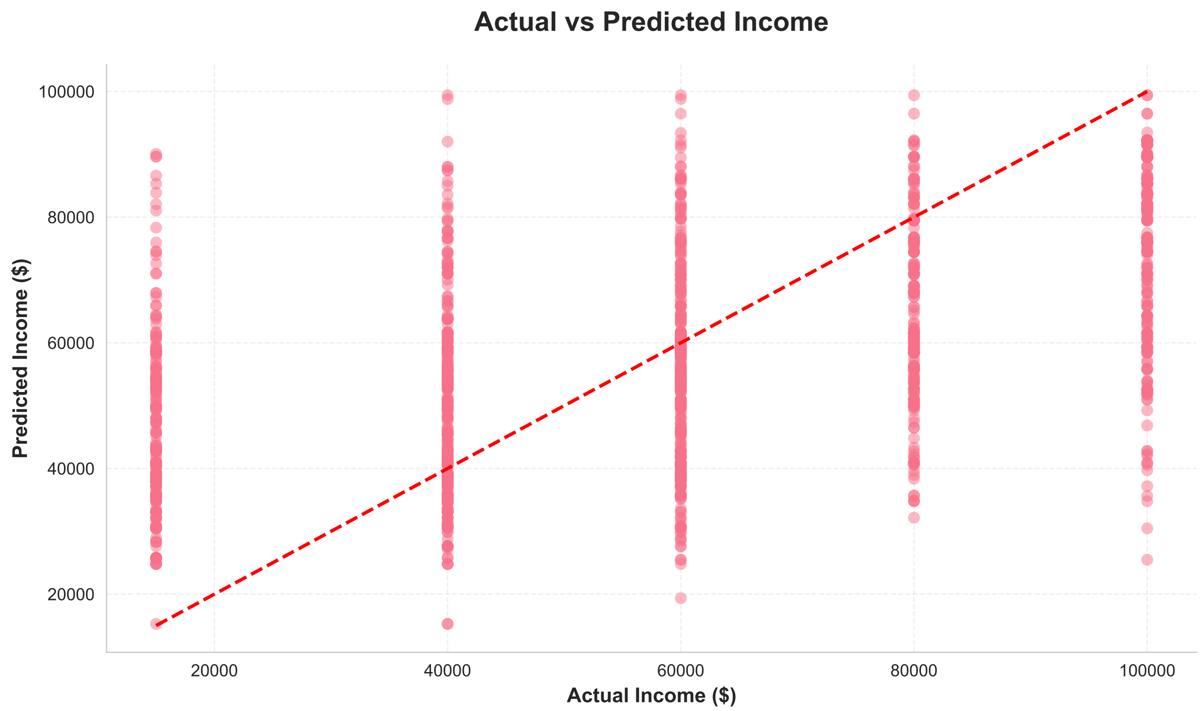



```
Using the following features for modeling: ['GENDER2', 'CERTLEVP', 'GRADAGEP', 'VISBMINP', '

=== Predictive Modeling: Income Prediction ===

Removed job-related features: ['JOBINCP', 'LFCINDP', 'LFCOCCP', 'LMA6_11']
Using features: ['Gender after distribution of non-binary persons', '2020 Program - Level of
1. SelectKBest Feature Selection:
Selected features: ['2020 Program - Level of study - Grouping', '2020 Program - Age at time

2. Recursive Feature Elimination (RFE):
Selected features: ['Gender after distribution of non-binary persons', '2020 Program - Level

3. Random Forest Feature Importance:
```

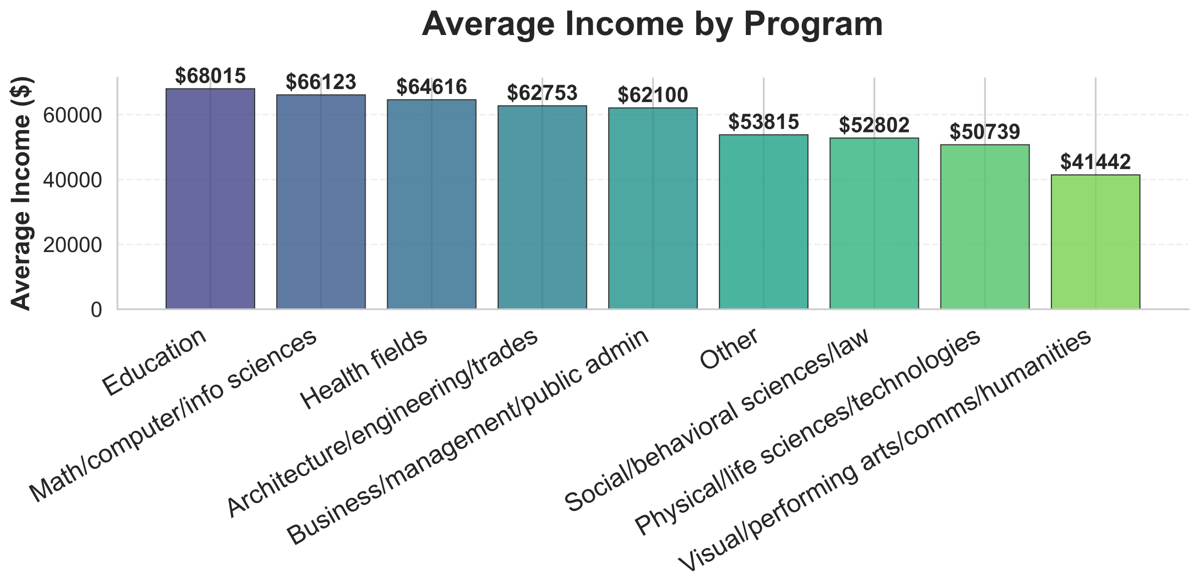



```
Top 5 features: ['2020 Program - Level of study - Grouping', '2020 Program - Aggregated CIP

4. Model Performance Comparison:
All features RMSE: $23668.64, R²: 0.252
Top 5 features RMSE: $22978.14, R²: 0.295
SelectKBest features RMSE: $23148.84, R²: 0.284
RFE features RMSE: $23134.13, R²: 0.285
```

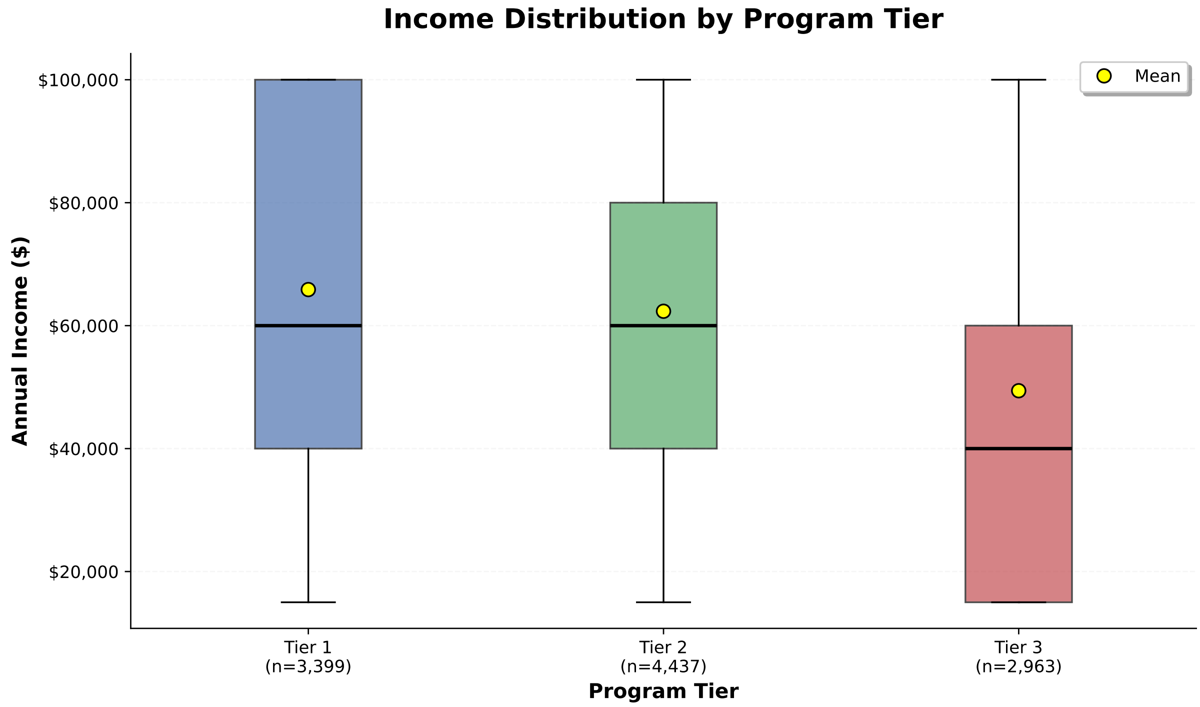





```
=== Income Outcomes by Program ===
```




```
Programs by Average Income (with sufficient data, n > 50):
Education: $68015 (n=957.0)
Math/computer/info sciences: $66123 (n=659.0)
Health fields: $64616 (n=1783.0)
Architecture/engineering/trades: $62753 (n=1618.0)
Business/management/public admin: $62100 (n=2819.0)
Other: $53815 (n=658.0)
Social/behavioral sciences/law: $52802 (n=1608.0)
Physical/life sciences/technologies: $50739 (n=575.0)
Visual/performing arts/comms/humanities: $41442 (n=780.0)

Note: 9 programs had sufficient data (>50 respondents)

No programs had limited data (<=50 respondents).

=== Income by Program Tier ===
```




```
Detailed Income Statistics by Program Tier:
--------------------------------------------------
Tier 1:
  Count: 4,212
  Mean: $65,865
  Median: $60,000
  Std Dev: $27,414
  25th Percentile: $40,000
  75th Percentile: $100,000

Tier 2:
  Count: 5,420
  Mean: $62,338
  Median: $60,000
  Std Dev: $26,621
  25th Percentile: $40,000
  75th Percentile: $80,000

Tier 3:
  Count: 3,647
  Mean: $49,411
  Median: $40,000
  Std Dev: $27,121
  25th Percentile: $15,000
  75th Percentile: $60,000
```

```
=== Key Findings ===
1. Tier 1 graduates earn $65,865 on average, which is $3,527 more than Tier 2 and $16,454 mo
2. Tier 3 graduates have the lowest median income ($40,000) and the highest income variabili
3. 25% of Tier 3 graduates earn less than $15,000, indicating more financial instability in 
4. Despite similar median incomes, Tier 1 graduates have higher earning potential with 25% e
```

8 Conclusion

This project successfully transitions the NGS dataset from a static repository of information into a dynamic tool for strategic decision-making. The creation of an interactive dashboard ensures these insights remain accessible for ongoing exploration.

The central, unequivocal finding—that field of study is the primary engine of post-graduation success—provides a powerful, data-driven lens through which to view our program offerings, clearly identifying areas of strength and opportunity. **This conclusion holds despite the inherent limitations of self-reported data and the methodological challenges of predictive modeling, underscoring the strength of this core relationship.**

The path forward is clear. We must act on these insights by:

1. Strategically amplifying our high-demand, high-outcome programs
2. Innovating and enhancing programs with greater market challenges through curriculum integration and robust career support
3. Empowering students with this data to make informed decisions about their educational investment

By embedding these insights into our academic strategy, student support, and marketing communications—with a clear understanding of the data's scope and constraints— we commit to a future of continuous improvement. This nuanced, data-driven approach will not only elevate graduate outcomes but also solidify our reputation as an institution dedicated to delivering tangible, lifelong value.